indicator is included to test for differences in cost growth between treatment and control firms prior to CDHP offer in the treatment firms. The key identifying assumption is that treatment firms would have had the same time trends as control firms in the absence of CDHP offer by treatment firms. In the next section, we describe a novel machine learning based approach that mitigates the possibility that this identifying assumption is violated.

We estimate (1) for total annual health care costs and separately on health care costs for each of the four types of care (outpatient, inpatient, emergency department, or prescription drugs). To test for differential effects by strength of CDHP incentive, we estimate (1) with *Post1*, *Post2*, and *Post3* interacted with a) personal medical account type (HSA or HRA), b) employer contribution to personal medical accounts (above or below median contribution), and c) effective deductible (above or below median). In these additional models, the coefficients of interest are the treatment interaction terms and the total effects by type of treatment.

We also estimate the impact of CDHP enrollment, rather than offer, under the additional assumption of no spillovers of the CDHPs onto employees at CDHP offering firms who are not CDHP enrollees. To estimate this local average treatment effect (LATE), researchers often turn to an instrumental variables approach where treatment offer is an instrument for enrollment (Finkelstein et al. 2012). This two stage least squares approach is not feasible in our setting as we are estimating a non-linear model with three binary endogenous regressors and three binary instruments. Instead, we estimate the LATE by dividing the DiD estimates (Table 3) by the average take-up rates in the relevant firm year.

5.2. A Machine Learning Approach to Achieve Consistent Within Firm Composition Over Time

The firms in our study are large, most with multiple locations, and many with a significant proportion of lower income employees. Due to employee turnover and firm acquisitions, the employees and dependents of each firm change over time. As a result, our estimates may capture both the effects of CDHPs and changes in composition if the firm fixed effects and a simple specification of the time varying person-year level covariates are insufficient to address year-to-year fluctuations in the composition of employees. For example, it is possible that younger employees leave control firms at a higher rate than treatment firms. CDHPs' lower premiums may be particularly attractive to younger employees who on average have lower incomes and relatively little need for health care, which may lead to higher retention of these employees. If this is the case then we would not be able to distinguish the effects of differential retention of young employees from the true CDHP effect.

One approach for dealing with attrition and other changes in composition would be to investigate a continuously enrolled cohort in CDHP and control firms over the entire sample period. However, a continuously enrolled population may differ in observed and unobservable ways from those with incomplete enrollment over the sample period; this is particularly true given the long time span we examine. Instead we use a novel approach that reduces potential bias in the difference-in-differences estimates by keeping a close approximation to the (weighted) joint distribution of covariates of individuals receiving coverage through each firm constant over time. Because the procedure balances the full joint distribution, it removes reliance on the particular specification of covariates in the outcome model. The balancing weights stand in for the set of potentially complex non-linear interactions required to obtain balance in the joint distribution of covariates over time for every firm. In this sense, we ensure that the firm fixed effects 'work' in that they are representing sets of individuals whose joint distribution of observed covariates is time-invariant. To our knowledge, this is the first paper to identify and control for this source of potential bias in a more systematic way than firm fixed effects and/or simply specified regression control for individual level observed covariates.

Our approach proceeds as follows. For each treatment firm we assign weights to those present in each non-baseline year such that, after weighting, the joint distribution of covariates for each non-baseline year matches that observed in the firm's baseline year (year prior to CDHP offer). Similarly, we assign weights to the individuals in each year in each control firm to match the joint distribution of covariates for individuals in that firm observed in 2005 (the middle of the study period as there is no baseline year defined by initiation of treatment). The models used to create the weights were estimated separately for each employer and each pair of years (the baseline and a single non-baseline year). As a result, the cost growth we observe after weighting removes the effects of changes in observed socio-demographics, zip code characteristics, or geographic location of employees and their dependents from year to year. This makes the CDHP effect 'doubly-robust' as if either the models predicting year for each pair of years for each firm or the cost model specification of the individual level covariates is correct, and the observed covariates are sufficient, then the treatment effect estimate will be unbiased (Kang and Schafer 2007).

To construct the weights, we use a statistical machine learning methodology, generalized boosted regression (implemented in a streamlined version of the R package TWANG[6]). Using generalized boosted regression in this context is preferable to the more commonly estimated Logit model for two reasons. First, generalized boosted regression fits highly flexible models

[6] http://cran.r-project.org/web/packages/twang/vignettes/twang.pdf.

incorporating complex interactions of the covariates, leading to weights that produce better balance on the full joint distribution rather than just the marginal for each variable individually (McCaffrey et al., 2004). Second, this method produces a distribution of weights that are less extreme and hence less able to cause variance inflation, a well-known problem with the Logit (Lee et al. 2011). Generalized boosted regression is an iterative procedure where the stopping rule is based on the degree of success in creating covariate balance. At each iteration, the procedure searches over simple regression tree models, each fit to the residuals from the model in the prior iteration, and selects the one that best improves the fit of the model to the data. Regression trees describe the relationship between a dependent variable and covariates by partitioning observations into regions defined by values of the covariates. That new regression tree adjustment is added to the model at the prior iteration to create the new model. The final model is the additive sum of the collection of simple regression tree models each one providing the best improvement at its iteration (McCaffrey et al. 2004). There are different metrics used to establish balance for the stopping rule and while the standardized difference in means is common, we chose to use the KS statistic, a measure of the extent of differences in the cumulative distribution functions of two variables or sets of variables, as the criteria for stopping the process in order to balance the full distributions of covariates, not just their means. The methodology also allowed us to identify situations in which changes over time within firm were too fundamental to be balanced and we dropped such firm-years from the analysis based on there being any covariate, which had a KS statistic greater than 0.05.[7]

[7] See table A1 for the effect of this and all other data restrictions on the resulting analytic sample

We achieved excellent balance on covariates[8] within firm over time[9]. Appendix Figures A1-3 through A1-6 plot the distribution of the balance statistics for control and treatment firms that were retained. As the figures demonstrate, balance was good to start with in many instances and the methodology greatly reduced the differences in standardized effect sizes and KS statistics when they were present. We apply these weights in all descriptive statistics and models.

5.3. Sensitivity of results to balanced panel of firms

As described above, the firms in our data offer CDHPs in different calendar years while the data window is fixed in calendar time. In the models, we include the largest number of pre- and post-CDHP years available in the data. This means we estimate the post-offer effects using an unbalanced panel (i.e., different firms identify each year's effect). To be more specific, the estimated first-year effect is identified by 24 firms, the second year effect by 20 of those firms, and the third year effect by 13 of those firms. Thus in our main specification, any differences in the second or third year effect relative to the first year effect could be the result of changes in CDHP effects over time and/or changes in firm composition. In order to distinguish between these sources of change, we re-estimate the main models twice, first restricting to only those firms with at least two years of data following CDHP offer and second restricting to only those firms with at least 3 years of data following CDHP offer.

6. Description of the Sample and the Treatment

[8] We balanced on gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), % White (zip), 9 census region dummies and a dummy for being in an MSA.

[9] The generalized boosted regression procedure has tuning parameters: we set the maximum regression tree level at 2, the shrinkage at 0.01, and the bagging fraction at 1.

Table 1 presents descriptive statistics for the weighted sample, stratified by treatment status. The roughly five million treatment individuals look fairly similar on observables to the eight million control individuals. The enrollees at CDHP offering firms are slightly older, more likely to be without children, and reside in zip codes with a lower median household income.

Figure 1 demonstrates that the weighted cost growth in control firms is very similar to that seen in the private insurance market nationally over this time period (CMS, 2013), suggesting strong external validity. Figure 2 shows that the cost growth for control firms is also similar to that for the subset of treatment firms for which we have two years of data prior to the CDHP offer. This supports the key assumption of the difference-in-difference identification strategy. While not an assumption required for our identification strategy, the average cost *levels* in the baseline year are also similar: $3,051 (SE = $472) for control firms and $3,284 (SE = $518) for treatment firms.[10]

Figure 3 and Table 2 summarize the nature of the CDHP offer. Averaged across all employees and dependents of CDHP offering firms, offering a CDHP is associated with a 2-3 fold increase in average deductibles (Figure 3). In contrast, average deductibles increase smoothly and quite gradually in the control firms. Average deductibles increase from the 1st to 3rd year post offer among the treatment firms because of increases in the proportion of employees enrolling in CDHPs (Table 2).

The remaining columns of Table 2 summarize the key features of the CDHPs being offered in each treatment year. In the first two years of offer, the mix of HSAs and HRAs is approximately 50/50, average employer account contributions are approximately $150 and

[10] Standard errors are calculated as the standard deviation of the firm means divided by the square root of the number of firms.

average effective deductibles are close to $1,000. We have data for 13 of the 24 treatment firms for a third year post offer. These firms have a higher proportion of HRAs than HSAs and more generous employer account contributions. For additional information on changes in firm composition over time see Appendix Table A3-1.

7. Results

7.1. Intent-to-treat effect

Relative to control firms and the pre-offer years, firms offering a CDHP had an estimated 6.6, 4.3, 3.4 percent lower annual spending in the first three years respectively ($p < 0.05$ for each difference) (Table 3, column 1). In addition, the CDHP second pre-year trend coefficient is insignificant, supporting the assumption of a parallel trend in the absence of CDHP offer. In section 6.4 below, we discuss whether the post CDHP offer impact is changing over time controlling for differential composition of treatment firms over time.

The CDHP effect varies considerably across spending category. Relative to non-offering firms, annualized spending growth on pharmaceuticals is 5 to 9.5 percentage points lower in the three years after firms offer CDHPs ($p < 0.01$) and spending growth on outpatient care is 3.0 to 6.8 percentage points lower in the first three years though the estimate loses statistical significance in the third year ($p < 0.05$ in first two years). In contrast, for inpatient cost growth, we have only marginally statistically significant evidence of lower spending relative to non-offering firms in the first two years of CDHP offer ($p < 0.10$) while the third year estimate is non-significant and very close to zero. Finally, we do not detect any differences in cost growth for emergency department (ED) care in any of the first three years of CDHP offer although, due to high variance in ED spending, estimates are imprecise.

7.2. Local average treatment effect

The results in Table 4 indicate how large the impact on cost growth would be for those *enrolled* in CDHPs if they were the only ones contributing to the reduced cost growth, i.e. if there were no spillovers to employees offered but not enrolled in CDHPs. These estimates range from 7 to 22 percentage point reductions in health care cost growth in the first three years of enrollment in a CDHP ($p < .005$, standard errors range from 3 to 9 percentage points).

In columns three and four (Table 4), we estimate an additional intent to treat model including only the five firms who have a high CDHP takeup. [11] For these firms any contributions of spillovers to CDHP offer effects would be limited. As expected, the intent-to-treat estimates are larger, ranging from 9 to 13 percentage point reductions in cost growth ($p<0.01$). However, the local average treatment effect estimates are similar to those for the full sample (none of the effects are significantly different from the full sample estimates). This finding supports the hypothesis that the reductions in cost growth may be attributable primarily to CDHP enrollees rather than spillovers to those enrolled in other plans.

7.3. Differential Impact of CDHP by Degree of Cost Sharing Incentives

In Table 5, we consider whether CDHP design features lead to differential impact on spending. Each row displays the estimated first, second, and third year CDHP offer effects stratified on whether an HRA or HSA was offered, employer account contribution, and effective deductible. These are calculated using post-estimation from models with CDHP offer interaction terms (see Appendix Tables A2-4, A2-5, and A2-6 for those results). There are no statistically

[11] Five firms met the high takeup criteria of being above the 75%tile of take-up in all available post years. The mean take-up rates in these firms were 90%, 92%, and 95% in the first, second, and third post years, respectively.

significant differences in CDHP effects across any of these three specifications. However, the pattern of results suggests greater cost reductions that last longer for firms offering CDHPs with HSAs (rather than HRAs), with lower employer contributions to personal medical accounts, and with higher effective deductibles.

7.4. Testing sensitivity to balanced firm panel

The models in which we restrict the treatment group to only include firms with at least 2 years of data post CDHP offer or with at least 3 years of data post CDHP offer are shown in Appendix Tables A3-2 and A3-3. When we restrict to firms with at least 2 years of data post CDHP offer, the year 1 post-offer effects on total costs and costs of each component of health care are very similar to the full sample results (Table A3-2). This is not surprising as only four firms are lost. The 20 firms with at least 2 years of post CDHP offer data are similar to the full sample of 24 firms in CDHP take-up, HRA/HSA mix, and employer contribution to personal medical accounts (Table A3-1). In contrast, the impact in the first and second years of CDHP offer for the 13 firms with three years of data post offer are smaller (closer to zero) and less often statistically significant compared with the full sample of 24 firms. Compared to the full sample, the 13 firms with 3 years of post-CDHP offer data were more likely to pair the plans with HRAs versus HSAs and to give greater employer account contributions.

While the point estimates for Years 1, 2, and 3 post-offer are monotonically decreasing with time since offer, the change in firm composition just discussed complicates any interpretation of this pattern. With the full sample (Table 3), we cannot reject that the CDHP offer effects are the same in each of the three years post offer ($0.09 < p < 0.34$). This is because the third year estimates are available for only 13 out of 24 CDHP firms. These 13 firms offered CDHPs with systematically weaker incentives than those first offered later in the study period. Thus the change in point estimates overtime could reflect this change in firm composition.

However, when we restrict the sample to just a balanced panel of the 13 firms, we again find that the CDHP effect point estimates monotonically decrease overtime. Again the differences between the years are not statistically significant. Overall based on this analysis we conclude that there is weak evidence that the cost saving effects of CDHPs diminish overtime and moderate evidence that they do not increase over time.

8. Summary and Discussion

With health care costs continuing to grow faster than GDP (CMS 2014; BEA 2014) it is critical to understand the effectiveness of cost-reduction strategies. Prior literature has established that CDHPs reduce spending in the short term. However, the longer term impacts are less clear. There has been concern that CDHP enrollees will decrease their use of necessary care and this will result in increased spending in the long term due to greater complications.

This study substantially adds to our knowledge on the long term cost impacts of CDHPs. We estimated spending trends for three years across over 13 million people across the country in an analysis estimating CDHP impacts without the threat of individual level selection bias. We find that health care cost growth among firms *offering* a CDHP is significantly lower in each of the first three years after offer. This result suggests that, at least at large employers, the impact of CDHPs persists and is not just a one-time reduction in spending. However, an important caveat is that the decrease in spending may be smaller in year 3 compared to year 1 post-offer. Recognizing that the differences are not statistically significant, these results are suggestive and consistent with a decreasing impact of CDHPs over time.

The decreases in total spending growth observed are primarily due to reductions in spending on outpatient care and pharmaceuticals. In contrast, by the third year there are no differences in either emergency department or inpatient spending. There are several potential explanations for this differential impact depending on whether reductions in costs are achieved through price shopping, switching to higher-value treatment options, or blanket reductions in care. Pharmaceutical spending is ideally suited for learning over time as chronic medications are purchased regularly and price information is fairly accessible (Huckfeldt et al. 2015). Also, generic drugs, where available, provide a clearer signal regarding value than most treatment options. Some patients may also believe that taking their medications less regularly has little health consequence, although research has shown that cost-sharing induced reductions in pharmaceutical use can lead to increased hospitalizations (Chandra et al. 2010). In contrast, emergency department care and inpatient care may be less amenable to any of the three mechanisms for reducing costs. It is difficult to obtain price information and in many instances the care is emergent making it impossible to shop for care. In addition, the incentives to reduce spending might be limited as the cost of one inpatient episode will typically be greater than the deductible. Outpatient care is intermediate between these two extremes. Outpatient physician visits tend to be repeated more than inpatient care but less than pharmaceutical purchases, perceptions of the harms of reducing care are likely to be similarly intermediate, and price and quality information is difficult to obtain.

Our results on the differential impact of CDHP design features on spending are not statistically significant. However, our estimates are consistent with what theory would suggest: CDHPs with larger financial incentives are associated with greater and more long lasting reductions in spending than CDHPs with smaller financial incentives. As families increasingly enroll in CDHPs with a variety of design features, further research is needed to determine which structures are most beneficial.

The magnitude of the first year effects we observe are consistent with most prior research investigating the short-term effect of CDHPs. Similar to LoSasso et al. (2010), Charlton et al. (2011), and Fronstin et al. (2013) and contrary to Borah et al. (2011), we find reductions in health care cost growth beyond the first year of CDHP offer. Contrary to Wharam et al. (2011, 2013), Kozhimannil et al. (2013), and Reddy et al. (2014), we do not detect any reductions in emergency department spending over three years[12]. Our findings on inpatient spending are consistent with Wharam et al. (2011, 2013). We find reduced spending in the first two of three years post offer and they detect reductions in inpatient utilization for the first of two years. In contrast, in their Harvard case study, Kozhimannil et al. (2013) and Reddy et al. (2014), find increases in inpatient use in the second year. The differences between our study and these particular prior studies may be due to their use of HMO rather than low deductible PPO enrollees as the comparison group, individual level selection in the Harvard studies or the difference in firm sizes for the Wharam studies.

Our final contribution is methodological, the novel application of a machine learning technique to mitigate potential violations of the identification assumption (that treatment units would have had the same trend in outcomes over time as controls if they had not offered the treatment). This procedure reduces sensitivity of results to the regression specification for covariates in outcome models, strengthens the effectiveness of fixed effects (such as firm fixed

[12] Although several of these studies are on ED use, not costs.

effects) in reducing potential bias in difference in difference designs, and is relatively accessible for economists without a background in machine learning.

The results presented here are limited to large employers and therefore may not extend to Medicaid beneficiaries, the individual or small group market, or to the health insurance exchanges where, on average, deductibles and out of pocket maximums are higher and/or enrollees have fewer financial resources. While the firms in this study were specifically selected to have lower income employees, all families had at least one adult working full time with benefits so they are typically better off than families not offered employer sponsored insurance.

In summary, in the first large multi-employer study to investigate long term CDHP spending impacts we find reductions in health care cost growth in all three years post CDHP offer and do not detect increases in any component of health care spending. These findings do not support either the concern that decreases in spending will be a one-time occurrence or that short-term decreases in spending with a CDHP will result in increases in spending in the long term due to complications of forgone care. We cannot rule out either of these concerns developing over an even longer time frame.

References

Americas Health Insurance Plans. 2014. "An Analysis of Health Savings Account Balances, Contributions, and Withdrawals in 2012." Center for Policy and Research.

Borah, Bj., ME Burns, and N. D. Shah. 2011. "Assessing the Impact of High Deductible Health Plans on Health-Care Utilization and Cons: A Changes-in-Changes Approach." *Health Economics* 20(9): 1025-42

Bundorf, K., 2012. "Consumer Directed Health Plans: Do They Deliver." The Robert Wood Johnson Foundation Research Synthesis Report No. 24

Buntin, M., A. Haviland, R. McDevitt, and N. Sood. 2011. "Health Care Spending and Preventive Care in High-Deductible and Consumer-Directed Health Plans." *American Journal of Managed Care* 17(3): 222-30

Chandra, A., J. Gruber, and R. McKnight. 2010. "Patient Cost-Sharing and Hospitalization Offsets in the Elderly." *American Economic Review* 100(1): 193-213.

Charlton, M.E., T. Levy, R.R. High, J.E. Schneider, and J.M. Brooks 2011. "Effects of Health Savings Account Eligible Plans on Utilization and Expenditures.' *American Journal of Managed Care* 17(1): 79-86.

Chen, S., RA. Levin, and JA. Gartner. 2010. "Medication Adherence and Enrollment in a Consumer-Driven Health Plan." *American Journal of Managed Care* 16(2) 43-50.

CMS. 2013. "Table 1 National Health Expenditures; Aggregate and Per Capita Amounts, Annual Change and Percent Distribution: Selected Calendar Years 1960-2012." Centers for Medicare and Medicaid Services. http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/tables.pdf

Cutler, D. and N.R. Sahni 2013. "If Slow Rate of Health Care Spending Growth Persists." *Health Affairs* 32(5): 841-50.

Finkelstein, A., S. Taubman, B. Wright, M Bernstein, J. Gruber, J. Newhouse, H. Allen, K. Baicker, and The Oregon Health Study Group. 2012. "The Oregon Health Insurance Experiment: Evidence from the First Year." *The Quarterly Journal of Economics* 127(3): 1057-1106.

Fronstin, P. (2014). "Health Savings Accounts and Health Reimbursement Arrangements: Assets, Account Balances, and Rollovers, 2006-2013." *EBRI Issue Brief* no. 395.

Fronstin, P., M.-J. Sepulveda, and M.C. Robebuck. 2013. "Medical Utilization and Adherence in a Health Savings Account-Eligible Plan." *American Journal of Managed Care* 19(2): 400-07.

Haviland, A., M.S. Marquis, R.D. McDevitt, and N. Sood. 2012. "Growth of Consumer Directed Health Plans to One-Half of All Employer-Sponsored Insurance Could Save $57 billion Annually." *Health Affairs* 31(5): 1009-15.

Haviland, A., N. Sood, R. McDevitt, and S.M. Marquis 2011. "How Do Consumer Directed Health Plans Affect Vulnerable Populations." *Forum for Health Economics & Policy*. 14(2) (Online): 1558-9544.

Huckfeldt, P., A. Haviland, A. Mehrotra, Z. Wagner, and N. Sood, 2015. "Patient Responses to Incentives in Consumer-Directed Health Plans: Evidence from Pharmaceuticals. Working Paper.

Kang, J., Schafer, J. 2007. "Demystifying Double Robustness: A Comparison of Alternative Strategies for Estimating a Population Mean From Incomplete Data." *Statistical Science*. 22(4): 523-39.

KFF, HRET. 2014. "Employer Health Benefits: 2013 Summary of Findings." The Kaiser Family Foundation and Health Research and Education Trust

Kozhimannil, K. B., M. R. Law, C. Baluer-Patterson, F. Zhang, J.F. Wharam. 2013. "The Impact of High Deductible Health Plans on Men and Women: An Analysis of Emergency Department Care." *Medical Care* 51(8): 639-45.

Lee, B.K., J. Lessler, and E.A. Stuart. 2011. "Weight Trimming and Propensity Score Weighting." *PLos ONE* 6(3): e18174 doi: 10.1371/journal.pone.0018174.

Lo Sasso, A., L.A. Helmchen, and R.Kaestner. 2010. "The Effects of Consumer-Directed Health Plans on Health Care Spending." *The Journal of Risk and Insurance* 77(1): 85-103.

Manning, W. G., J. P. Newhouse., N. Duan, E. Keeler, B. Benjamin, A. Leibowitz, M.S. Marquis, J. Zwanziger. 1987. "Health Insurance and the Demand for Medical Care." *The American Economic Review* 77(3): 251-77.

McCaffrey, D.F., G. Ridgeway, and A.R. Morral. 2004. "Propensity Score Estimation With Boosted Regression for Evaluating Causal Effects in Observational Studies." *Psychological Methods* 9(4) 403-25.

McDevitt, R., A. Haviland, L. Laudenberger, R. Lore, M. Eisenberg, N. Sood. 2014. "Risk Selection into Consumer-Directed Health Plans: An Analysis of Family Choices within Large Employers." *Health Services Research*. 49(2): 609-27.

Newhouse, JP. *Free for All? Lessons from the RAND Health Insurance Experiment*. Cambridge, MA: Harvard University Press, 1993.

Parente, S., Feldman R. 2008. "Effects of a Consumer-Driven Health Plan on Pharmaceutical Spending and Utilization." *Health Services Research.* 43(5).

Reddy, S., D. Ross-Degnan, A. Zalaysky, S.B. Soumerai, and J.F. Wharam. 2014. "Impact of a High-deductible Health Plan on Outpatient Visits and Associated Diagnostic Tests." *Medical Care* 52(1): 86-92.

Reed, M., V. Fung, M. Price, R. Brand, N. Benedetti, S.F. Derose, J.P. Newhouse, and J. Hsu. 2009. "High-Deductible Health Insurance Plans: Efforst to Sharpen a Blunt Instrument." *Health Affairs* 28(4): 1145-1154. doi: 10.1377/hlthaff.28.4.1145

Reed, M.E., I. Graetz, V. Fung, J.P. Newhouse, and J. Hsu. 2012. "In Consumer-Directed Health Plans, A Majority of Patients were Unaware of Free or Low-Cost Preventive Care." Health Affairs 31(12): 2641-2648. doi: 10.1377/hlthaff.2012.0059

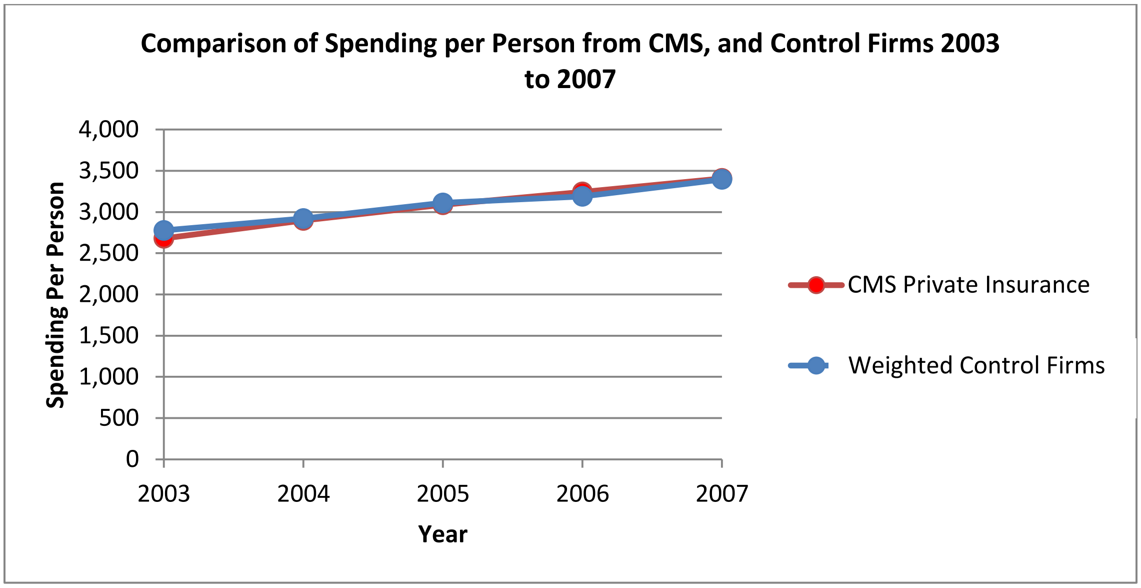
Whaley, C., J. S. Chafen, S. Pinkard, G. Kellerman, D. Bravata, R. Kocher, N. Sood. 2014. "Accociation Between Availability of Health Service Prices and Payments for These Services." *Journal of the American Medical Association* 312(16) 1670-76.

Wharam, J.F., B.E. Landon, F. Zhang, S.B. Soumerai, D. Ross-Degnan. 2011. "High-Deductible Insurance: Two-Year Emergency Department and Hospital Use."

Wharam, J. F., F. Zhang, B E. Landon, S. B. Soumerai, and D. Ross-Degnan. 2013. " Low-Socioeconomic-Status Enrollees In High-Deductible Plans Reduced High-Severity Emergency Care." *Health Affairs* 32(8): 1398-1406.

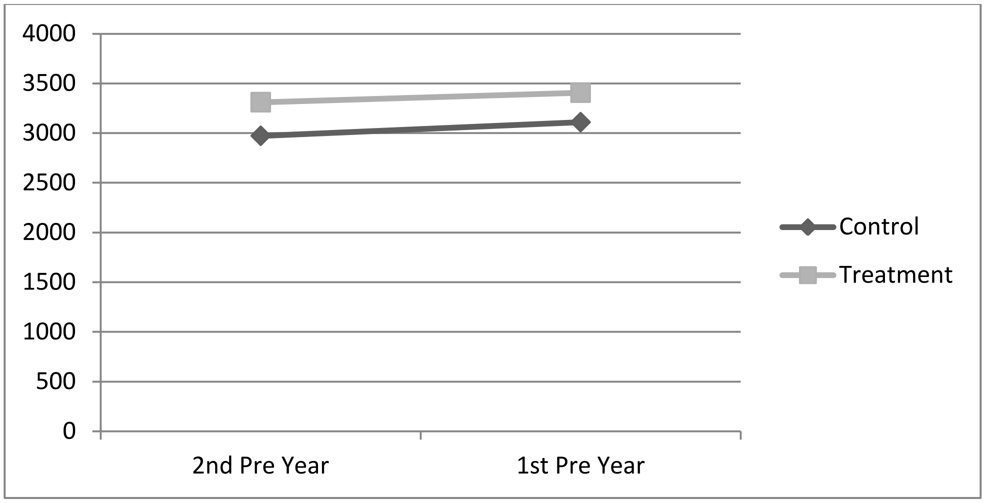
Figures

Figure 1: Control Firm Cost Trends Compared to National Data for Private Insurance



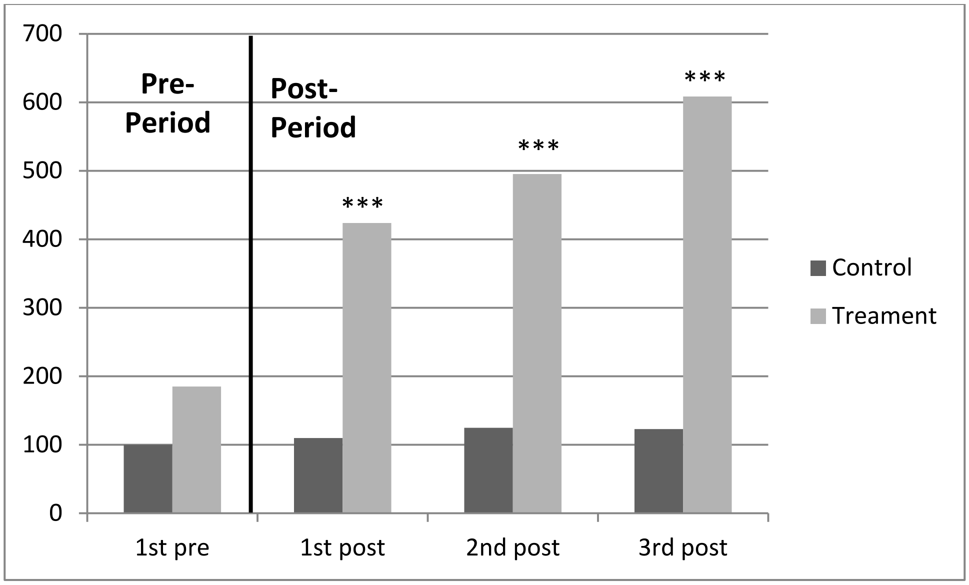
Notes: Source for CMS data is available at http://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/tables.pdf. This is the NHE Tables PDF. The specific table is Table 21 Medicare and Private Health Insurance; Per Enrollee Expenditures and Annual Percent Change, Calendar Years 1969-2011.

Figure 2: Comparison of Cost Trends Prior to CDHP Offer



Notes for 2a: The treatment line is mean total costs across the subset of treatment firms with 2 pre CDHP offer years available. The control line is the weighted average of average annual control firm costs, weighted by the distribution of calendar years within a CDHP offer year for the corresponding treatment firms. For example, the 1st Pre Year for the treatment firms is a combination of calendar years: 8% 2003, 68% 2004, and 24% 2005. To obtain the control mean for this '1st Pre Year', we take a weighted average of the control firm costs in 2003, 2004, and 2005 with weights of 0.08, 0.68, and 0.24, respectively.

Figure 3: Average Individual Deductible by Treatment Year



Notes: The treatment bars are the mean individual deductible for all employees at treatment firms. For those enrolled in CDHPs at treatment firms, the mean deductibles are $1426, $1492, and $1396 for the first, second, and third post year, respectively. Take up rates were 19.4%, 21.4%, and 34.6% in the first, second, and third post years. The control bars are the weighted average of average annual control firm individual deductibles, weighted by the distribution of calendar years within a CDHP offer year for the corresponding treatment firms (for example of weighted average calculation, see notes to figure 2). In a model including calendar year fixed effects and with standard errors clustered by firm, differences in deductibles between the treatment and control firms were statistically insignificant in the first pre-offer year ($p = 0.20$) and statistically significant in all three years post CHDP offer ($p < 0.001$).

Tables

Table 1: Description of the sample at the person-year level

	Controls (N=10,100,357)		Treatment (N=4,908,955)	
VARIABLES	Mean	SD	Mean	SD
Demographics				
Age	30.70	17.50	32.69	17.98
Female	0.504	0.500	0.501	0.500
Single Adult	0.133	0.340	0.135	0.341
Married, No Kids	0.137	0.344	0.146	0.353
Adult Male with Kids	0.0466	0.211	0.0498	0.217
Adult Female with Kids	0.0642	0.245	0.0516	0.221
Married, with Kids	0.617	0.486	0.6023	0.490
Median HH Income	52,120	18,915	51,373	17,249
% Unemployed	0.0470	0.0278	0.0471	0.0286
% College	0.282	0.162	0.255	0.148
% High School	0.565	0.112	0.588	0.101
% Hispanic	0.0793	0.132	0.0670	0.119
% Black	0.0950	0.156	0.102	0.182
% White	0.776	0.216	0.787	0.227
New England	0.0544	0.227	0.0228	0.149
Middle Atlantic	0.109	0.311	0.0515	0.221
East North Central	0.285	0.451	0.428	0.495
West North Central	0.0535	0.225	0.0890	0.285
South Atlantic	0.187	0.390	0.106	0.307
East South Central	0.0651	0.247	0.0526	0.223
West South Central	0.130	0.336	0.127	0.333
Mountain	0.0525	0.223	0.0223	0.148
Pacific	0.0620	0.241	0.0416	0.200
Unknown Location	0.00285	0.0533	0.0602	0.238
d(MSA)	0.875	0.331	0.819	0.385

Notes: Weighted means and standard deviations for the entire sample, all years (2003-2007) pooled. Statistics are calculated based on the weights described in section 4.2.

Table 2: Summary of Take-Up and Benefit Design Features of CDHPs Offered by Treatment Firms

	All Treatment Firm Individuals		Treatment Firm Individuals Enrolled in CDHPs			
	N	Take-up	HRA	HSA	Account Contribution	Effective Deductible
1st Post Year	1,269,190	0.194	0.592	0.408	157.2	991.8
					(267.7)	(359.9)
2nd Post Year	1,002,859	0.214	0.426	0.574	154.2	988.6
					(290.2)	(414.2)
3rd Post Year	480,535	0.346	0.724	0.276	262.2	821.7
					(318.5)	(306.9)

Notes: Summary for all available treatment firm years. Effective deductible is actual individual deductible minus the account contribution for an individual.

Table 3: GLM Models of CDHP Offer on Costs

VARIABLES	(1) Total Costs	(2) Outpatient Costs	(3) Drug Costs	(4) Inpatient Costs	(5) ED Costs
Treat*(2nd Pre Year)	-0.000640	-0.00726	0.0128	0.00945	-0.0369
	(0.0160)	(0.0144)	(0.0192)	(0.0236)	(0.0421)
Treat*(1st Post Year)	-0.0655**	-0.0675**	-0.0612***	-0.0638*	-0.0337
	(0.0256)	(0.0264)	(0.0173)	(0.0331)	(0.0833)
Treat*(2nd Post Year)	-0.0434***	-0.0405**	-0.0536***	-0.0536*	0.0620
	(0.0145)	(0.0204)	(0.0151)	(0.0322)	(0.115)
Treat*(3rd Post Year)	-0.0339**	-0.0303	-0.0949***	0.00197	0.0412
	(0.0142)	(0.0194)	(0.0236)	(0.0322)	(0.0673)
Proportion of Total Costs	1.00	0.53	0.23	0.20	0.04
Observations	13,553,830	13,553,830	13,553,830	13,553,830	13,553,830
Number of Firms	54	54	54	54	54

Notes: Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GLM Models estimated with a Gamma distributional assumption and log-link. We include a full set of firm fixed effects and year fixed effects. Controls include gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), and % White (zip). Location controls include full interactions between 9 census region dummies and an indicator for being in an MSA.

Table 4: Intent-to-treat and Treatment on the Treated Results (Assuming No Spillovers) for Total Costs

	(1)	(2)	(3)	(4)
	All Firms		High Take-up Firms	
	ITT	LATE	ITT	LATE
Treat*(1st Post Year)	-0.0655**	-0.2226**	-0.1300***	-0.1452***
	(0.0256)	(0.087)	(0.0236)	(0.0264)
Treat*(2nd Post Year)	-0.0434***	-0.1353***	-0.119***	-0.1300***
	(0.0145)	(0.0452)	(0.0200)	(0.0219)
Treat*(3rd Post Year)	-0.0339**	-0.0691**	-0.0852***	-0.0899***
	(0.0142)	(0.0289)	(0.0208)	(0.0220)

Notes: Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Local average treatment estimates (LATE) are calculated by taking the coefficient given in table 2a and dividing by average CDHP take up in that treatment year. Standard errors were derived using the delta method and the Stata command *nlcom.* Five firms met the high takeup criteria of being above the 75%tile of take-up in all available post years. The mean take-up rates in these firms were 90%, 92%, and 95% in the first, second, and third post years, respectively.

Table 5: Treatment Effects, Stratified by CDHP Account Features

	Account Type	
	HRA	HSA
1st Post	-0.0517***	-0.0705**
	(0.0177)	(0.0337)
2nd Post	-0.0287*	-0.0504**
	(0.0169)	(0.0197)
3rd Post	-0.0217	-0.0508***
	(0.0152)	(0.0183)
	Account Contribution	
	At <Median Account	At > Median Account
1st Post	-0.0958*	-0.0343**
	(0.0507)	(0.0157)
2nd Post	-0.0544**	-0.0353
	(0.0268)	(0.0251)
3rd Post	-0.0411	-0.0239
	(0.0347)	(0.0149)
	Effective Deductible	
	At <Median Effective Ded	At > Median Effection Ded
1st Post	-0.0317*	-0.0949**
	(0.0169)	(0.0477)
2nd Post	-0.0364	-0.0522**
	(0.0255)	(0.0233)
3rd Post	-0.0230	-0.0463
	(0.0146)	(0.0301)

Notes: Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Median account contribution is $500. Median effective deductible is $1,250. Full model estimates available in appendix table A2-4 and A2-5. Estimated using the STATA command *margins, eydx(*).* While different, none of the CDHP effects are significantly different from each other across account type.

Appendices

Appendix A1: Documentation of Preliminary Analysis Steps

Table A1-1: Sample Restrictions

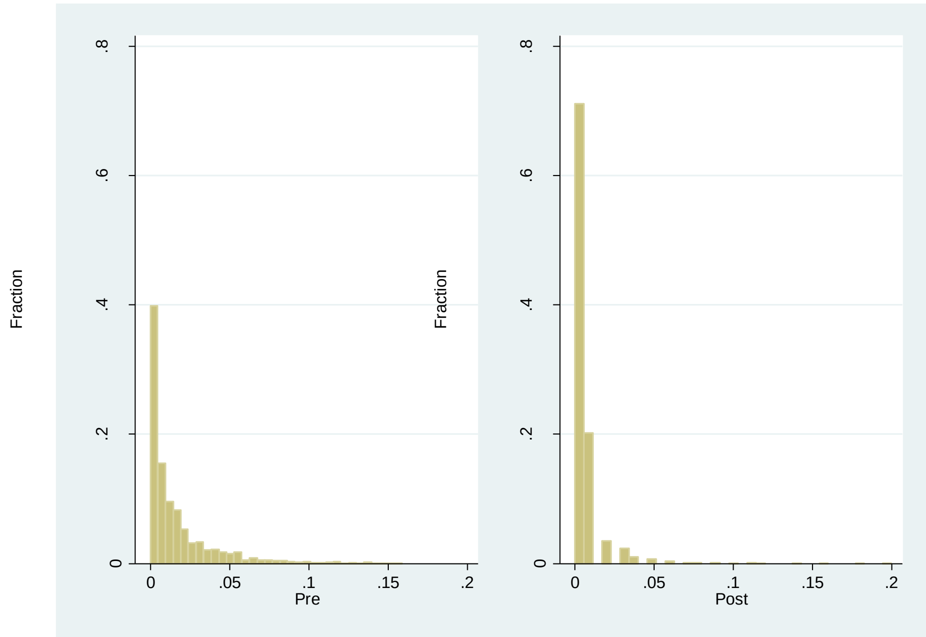
Restriction Type	Restriction	% of the Sample Dropped
Analysis Criteria	Person-years with less than one plan year of continuous enrollment	34%
Analysis Criteria	Person-years in a control firm and enrolled in a CDHP; in a treatment year, enrolled in a CDHP before firm offered; in a control firm with a high deductible; in a treatment firm with a high deductible before firm offered	0.4%
Data Anomalies	Person-years with missing plan information, irregular family structures	7.8%
Data Anomalies	Person-years with very high costs	.00117%
Data Anomalies	Firms for which we were unable to achieve adequate within firm balance on covariates over time	4.4%

Table A1-2: Fit Statistics From Candidate GLM Models

	(1) Gamma-Log	(2) Poisson-Log	(3) Normal-Log
Pre + Control†			
AIC	17.99	7191	21.52
BIC	-1.49e+08	7.46e+10	1.07e+15
Full Sample			
AIC	17.40	7096	20.80
BIC	-1.980e+08	9.590e+10	1.380e+15

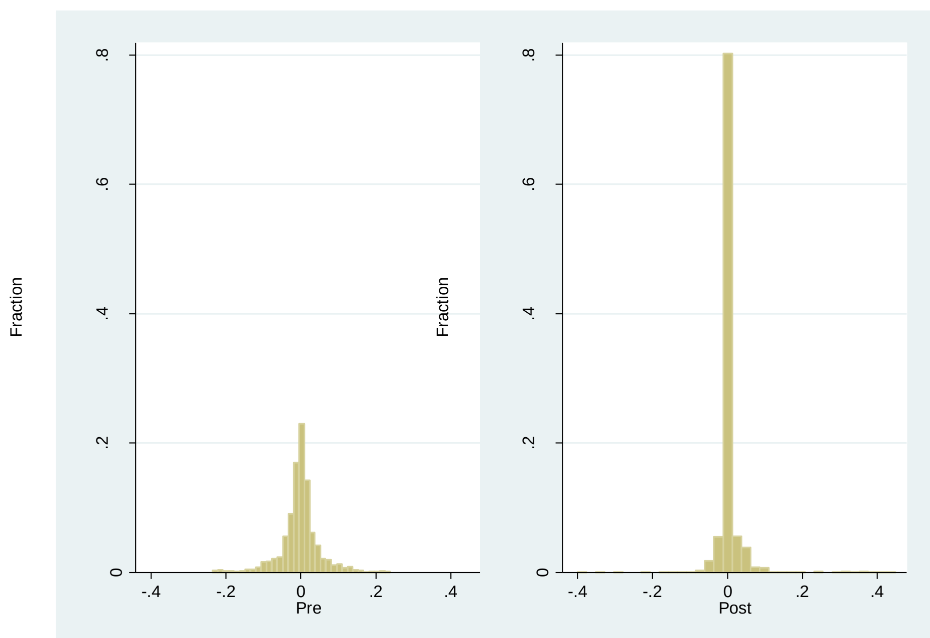
† Model selection was carried out using model runs including data for all years for control firms and data only for pre-CDHP offer years for treatment firms. We provide the full sample results for completeness.
Notes: These fit statistics come from the full total cost model from table 3 estimated with different GLM assumptions.

Figure A1-3: Histogram of KS Statistics, Control Firms, Before and After Weighting



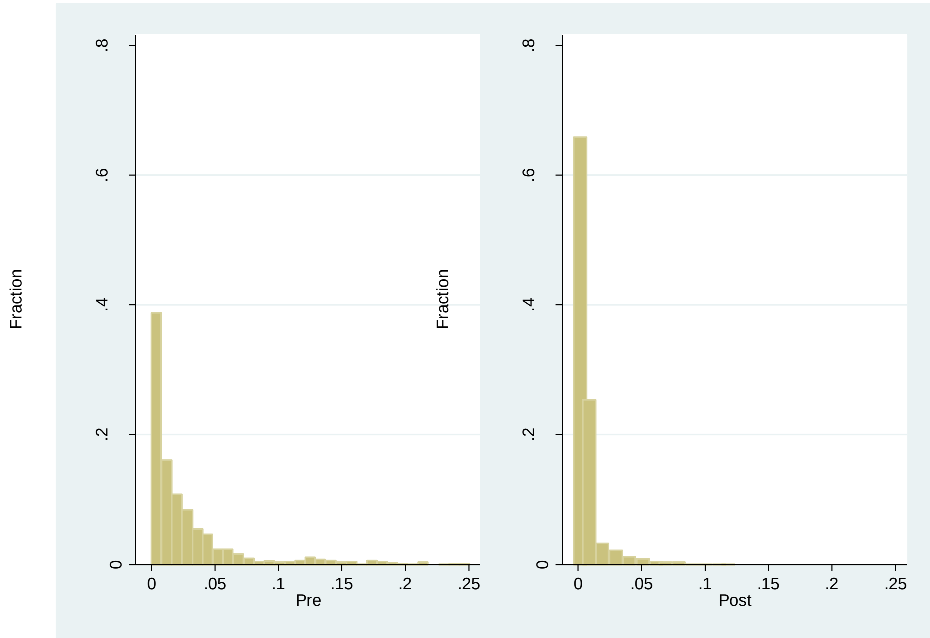
Notes: This figure presents the distribution of KS statistics across all control firms, all years, and all covariates. Pre weighting, the 99%tile was 0.16 and post weighting it was 0.1.

Figure A1-4: Histogram of Standardized Effect Size Differences, Control Firms, Before and After Weighting



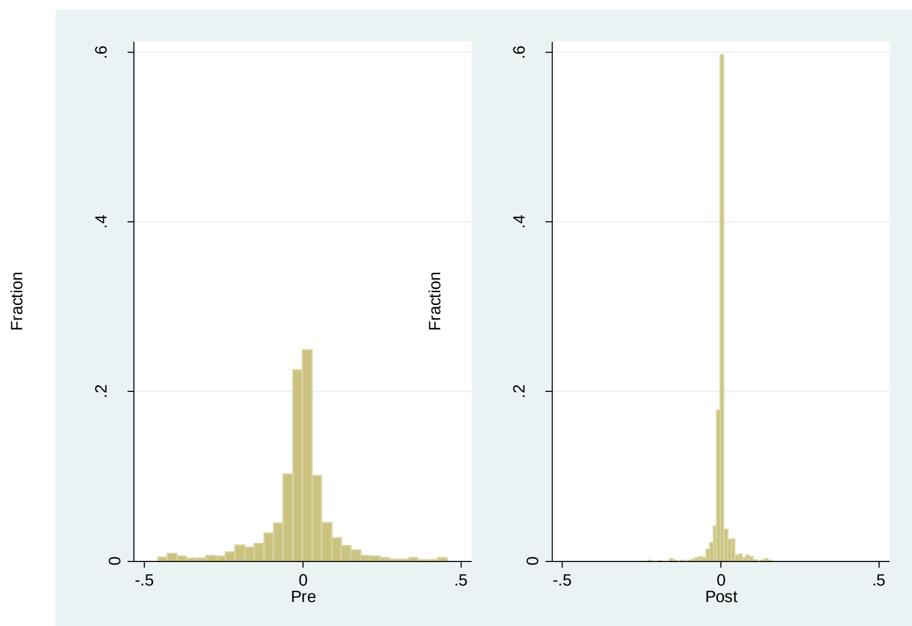
Notes: This figure presents the distribution of KS statistics across all control firms, all years, and all covariates. Pre weighting, the 99%tile was 0.24 and post weighting it was 0.14.

Figure A1-5: Histogram of KS Statistics, Treatment Firms, Before and After Weighting



Notes: This figure presents the distribution of KS statistics across all treatment firms, all years, and all covariates. Pre weighting, the 99%tile was 0.26 and post weighting it was 0.06.

Figure A1-6: Histogram of Standardized Effect Size Differences, Treatment Firms, Before and After Weighting



Notes: This figure presents the distribution of KS statistics across all treatment firms, all years, and all covariates. Pre weighting, the 99%tile was 0.46 and post weighting it was 0.10.

Appendix A2: Additional Results Related to Tables 3 and 4

Table A2-1: Full Model Results from Table 3

VARIABLES	(1) Total Costs
Treat*(2nd Pre Year)	-0.000640
	(0.0160)
Treat*(1st Post Year)	-0.0655**
	(0.0256)
Treat*(2nd Post Year)	-0.0434***
	(0.0145)
Treat*(3rd Post Year)	-0.0339**
	(0.0142)
Female	0.281***
	(0.0126)
Age	0.00880***
	(0.00162)
Age Squared	0.000316***
	(2.47e-05)
Married, No Kids	0.120***
	(0.0184)
Adult Male with Kids	-0.0866***
	(0.0231)
Adult Female with Kids	0.0427**
	(0.0167)
Married with Kids	0.155***
	(0.0372)
Median HH. Income (Zip)	4.22e-07
	(3.08e-07)
% Unemployed (Zip)	0.165
	(0.135)
% College (Zip)	-0.183***
	(0.0507)
% High School (Zip)	-0.226***
	(0.0733)
% Hispanic (Zip)	-0.0638
	(0.0748)
% Black (Zip)	-0.0135
	(0.0681)
% White (Zip)	0.159**
	(0.0677)
Middle Atlantic	-0.124***
	(0.0414)
East North Central	-0.0457
	(0.0355)

West North Central	-0.0485
	(0.0396)
South Atlantic	-0.00888
	(0.0380)
East South Central	0.00494
	(0.0427)
West South Central	0.0118
	(0.0448)
Mountain	-0.00627
	(0.0505)
Pacific	-0.139**
	(0.0602)
Unknown Location	-0.144**
	(0.0729)
d(MSA)	-0.127***
	(0.0321)
Middle Atlantic*d(MSA)	0.171***
	(0.0444)
East North Central*d(MSA)	0.138***
	(0.0331)
West North Central*d(MSA)	0.130***
	(0.0395)
South Atlantic*d(MSA)	0.0936**
	(0.0381)
East South Central*d(MSA)	0.101**
	(0.0414)
West South Central*d(MSA)	0.179***
	(0.0423)
Mountain*d(MSA)	0.0455
	(0.0570)
Pacific*d(MSA)	0.233***
	(0.0466)
2004	0.0688***
	(0.0135)
2005	0.144***
	(0.0118)
2006	0.182***
	(0.0140)
2007	0.256***
	(0.0129)
Observations	13,553,830

Table A2-2: Marginal Effects (in $ Terms)

VARIABLES	(1) Total Costs	(2) Outpatient Costs	(3) Inpatient Costs	(4) ED Costs	(5) Drug Costs
Treat*(2nd Pre Year)	-2.034	-12.27	6.129	-4.521	9.309
	(50.80)	(24.25)	(15.30)	(5.164)	(13.93)
Treat*(1st Post Year)	-208.2**	-114.0**	-41.35*	-4.129	-44.50***
	(81.55)	(44.61)	(21.48)	(10.21)	(12.59)
Treat*(2nd Post Year)	-138.1***	-68.47**	-34.73*	7.590	-38.93***
	(46.19)	(34.52)	(20.90)	(14.06)	(10.97)
Treat*(3rd Post Year)	-107.7**	-51.21	1.279	5.051	-68.96***
	(45.31)	(32.76)	(20.86)	(8.252)	(17.23)
Observations	13,553,830	13,553,830	13,553,830	13,553,830	13,553,830

Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Calculated from the estimates in Table 3. Marginal effects estimated using the Stata command *margins, dydx(*)* where these are dollar differences between the reported row and the omitted baseline (1st pre year).

A2-3: Fraction Enrolled in CDHP by Account Feature Groups each Treatment Year

	1st post Year	2nd post Year	3rd post Year
Account Type			
HRA	0.238	0.230	0.307
HSA	0.176	0.202	0.562
Account Contribution			
At <Median Account	0.188	0.247	0.759
At >Median Account	0.202	0.181	0.239
Effective Deductible			
At <Median Effective Ded	0.248	0.223	0.357
At > Median Effective Ded	0.143	0.203	0.279

Table A2-4: Cost Models with Account Type Interactions

VARIABLES	(1) Total Costs	(2) Outpatient Costs	(3) Inpatient Costs	(4) ED Costs	(5) Drug Costs
Treat*(2nd Pre Year)	-0.00318	-0.0102	0.00433	-0.0321	0.0150
	(0.0164)	(0.0152)	(0.0245)	(0.0396)	(0.0195)
Treat*(1st Post Year)	-0.0517***	-0.0473**	-0.0811**	0.00628	-0.0501*
	(0.0177)	(0.0209)	(0.0406)	(0.0535)	(0.0262)
Treat*(2nd Post Year)	-0.0287*	-0.0229	-0.00948	-0.0187	-0.0743***
	(0.0169)	(0.0202)	(0.0385)	(0.0827)	(0.0260)
Treat*(3rd Post Year)	-0.0217	-0.0169	0.0214	0.0543	-0.104***
	(0.0152)	(0.0208)	(0.0258)	(0.0788)	(0.0261)
Treat*HSA*(1st Post)	-0.0188	-0.0272	0.0201	-0.0481	-0.0135
	(0.0264)	(0.0415)	(0.0574)	(0.1203)	(0.0321)
Treat*HSA*(2nd Post)	-0.0218	-0.0258	-0.0677	0.124	0.0319
	(0.0264)	(0.0366)	(0.0518)	(0.180)	(0.0333)
Treat*HSA*(3rd Post)	-0.0291	-0.0252	-0.0609	-0.123	0.0305
	(0.0223)	(0.0375)	(0.0468)	(0.107)	(0.0391)
Demographics	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	13,553,830	13,553,830	13,553,830	13,553,830	13,553,830
Number of Firms	54	54	54	54	54

Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GLM Models estimated with a Gamma distributional assumption and log-link. Demographics include gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), and % White (zip). Location controls include full interactions between 9 census region dummies and a dummy for being in an MSA.

Table A2-5: Cost Models with Account Contribution Interactions

	(1) Total Costs	(2) Outpatient Costs	(3) Inpatient Costs	(4) ED Costs	(5) Drug Costs
Treat*(2nd Pre Year)	-0.00271	-0.00809	0.00314	-0.0353	0.0118
	(0.0180)	(0.0164)	(0.0277)	(0.0445)	(0.0200)
Treat*(1st Post Year)	-0.0958*	-0.0844	-0.103	-0.167**	-0.0878***
	(0.0507)	(0.0523)	(0.0635)	(0.0764)	(0.0297)
Treat*(2nd Post Year)	-0.0544**	-0.0420	-0.112*	0.137	-0.0514***
	(0.0268)	(0.0385)	(0.0610)	(0.213)	(0.0141)
Treat*(3rd Post Year)	-0.0411	-0.0437	0.0169	0.0752	-0.114***
	(0.0347)	(0.0375)	(0.0795)	(0.123)	(0.0397)
Treat*1st Post Year*Above Median Account Contribution	0.0615	0.0350	0.0728	**0.289***	**0.0556***
	(0.0530)	(0.0531)	(0.0725)	**(0.156)**	**(0.0327)**
Treat*2nd Post Year*Above Median Account Contribution	0.0191	0.00121	0.110	-0.145	-0.00659
	(0.0390)	(0.0449)	(0.0745)	(0.226)	(0.0298)
Treat*3rd Post Year*Above Median Account Contribution	0.0173	0.0201	-0.000876	-0.0143	0.0283
	(0.0389)	(0.0414)	(0.0864)	(0.148)	(0.0469)
Demographics	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Proportion of Total Costs	1.00	0.53	0.20	0.04	0.23
Observations	13,553,830	13,553,830	13,553,830	13,553,830	13,553,830
Number of Firms	54	54	54	54	54

Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GLM Models estimated with a Gamma distributional assumption and log-link. Demographics include gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), and % White (zip). Location controls include full interactions between 9 census region dummies and a dummy for being in an MSA.

Table A2-6: Cost Models with Effective Deductible Contribution Interactions

	(1) Total Costs	(2) Outpatient Costs	(3) Inpatient Costs	(4) ED Costs	(5) Drug Costs
Treat*(2nd Pre Year)	-0.00198	-0.00806	0.00651	-0.0371	0.0120
	(0.0171)	(0.0157)	(0.0255)	(0.0433)	(0.0198)
Treat*(1st Post Year)	-0.0317*	-0.0503***	-0.0215	0.143	-0.0274**
	(0.0169)	(0.0141)	(0.0401)	(0.128)	(0.0138)
Treat*(2nd Post Year)	-0.0364	-0.0353	-0.0296	0.0208	-0.0551**
	(0.0255)	(0.0250)	(0.0370)	(0.0723)	(0.0247)
Treat*(3rd Post Year)	-0.0230	-0.0250	0.0327	0.0688	-0.0955***
	(0.0146)	(0.0202)	(0.0265)	(0.0820)	(0.0227)
Treat*1st Post Year*Above Median Effective Deductible	-0.0632	-0.0323	-0.0807	**-0.322****	**-0.0625****
	(0.0505)	(0.0506)	(0.0699)	**(0.160)**	**(0.0317)**
Treat*2nd Post Year*Above Median Effective Deductible	-0.0158	-0.0114	-0.0507	0.0797	0.00142
	(0.0359)	(0.0447)	(0.0621)	(0.211)	(0.0303)
Treat*3rd Post Year*Above Median Effective Deductible	-0.0232	-0.00848	-0.115	-0.0505	0.0332
	(0.0312)	(0.0343)	(0.0747)	(0.104)	(0.0596)
Demographics	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Proportion of Total Costs	1.00	0.53	0.20	0.04	0.23
Observations	13,553,830	13,553,830	13,553,830	13,553,830	13,553,830
Number of Firms	54	54	54	54	54

Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GLM Models estimated with a Gamma distributional assumption and log-link. Demographics include gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), and % White (zip). Location controls include full interactions between 9 census region dummies and a dummy for being in an MSA.

Appendix A3: Models to Check Firm Composition Over Time

Table A3-1: Plan Descriptives by Treatment Cohort

All Firms	N	Takeup	HRA	HSA	Account Contribution
1st post Year	1,269,190	0.194	0.141	0.0792	157.2
					(267.7)
2nd Post Year	1,002,859	0.214	0.091	0.122	154.2
					(290.2)
3rd Post Year	480,535	0.346	0.251	0.0954	262.2
					(318.5)
Firms with at least 2 Post Years					
1st post Year	980,554	0.185	0.105	0.0795	126.3
					(264.9)
2nd Post Year	1,002,859	0.214	0.091	0.122	154.2
					(290.2)
3rd Post Year	480,535	0.346	0.251	0.0954	262.2
					(318.5)
Firms with 3 Post Years					
1st post Year	412,142	0.253	0.24	0.0127	290.2
					(337.8)
2nd Post Year	453,573	0.270	0.191	0.0786	290.7
					(350.6)
3rd Post Year	480,535	0.346	0.251	0.0954	262.2
					(318.5)

Table A3-2: Cost Models Restricted to Treatment Firms That Offer at Least Two Years (20 Treatment Firms)

VARIABLES	(1) Total Costs	(2) Outpatient Costs	(3) Inpatient Costs	(4) ED Costs	(5) Drug Costs
Treat*(2nd Pre Year)	0.0162	0.00412	0.0242	0.0268	0.0333*
	(0.0144)	(0.0155)	(0.0222)	(0.0302)	(0.0197)
Treat*(1st Post Year)	-0.0770**	-0.0759**	-0.0933**	-0.0872	-0.0593***
	(0.0324)	(0.0326)	(0.0407)	(0.0655)	(0.0222)
Treat*(2nd Post Year)	-0.0428***	-0.0399*	-0.0587*	0.0597	-0.0486***
	(0.0162)	(0.0221)	(0.0352)	(0.109)	(0.0154)
Treat*(3rd Post Year)	-0.0359**	-0.0317	-0.0085	0.0262	-0.0908***
	(0.0175)	(0.0216)	(0.0357)	(0.0612)	(0.0243)
Demographics	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	12,808,248	12,808,248	12,808,248	12,808,248	12,808,248

Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GLM Models estimated with a Gamma distributional assumption and log-link. Demographics include gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), and % White (zip). Location controls include full interactions between 9 census region dummies and a dummy for being in an MSA.

Table A3-3: Cost Models Restricted to Treatment Firms That Offer at Least Three Years (13 Treatment Firms)

VARIABLES	(1) Total Costs	(2) Outpatient Costs	(3) Inpatient Costs	(4) ED Costs	(5) Drug Costs
Treat*(1st Post Year)	-0.0369**	-0.0357**	-0.0520	0.0201	-0.0387
	(0.0176)	(0.0169)	(0.0452)	(0.0548)	(0.0242)
Treat*(2nd Post Year)	-0.0175	-0.0156	0.0207	-0.0299	-0.0566**
	(0.0147)	(0.0149)	(0.0334)	(0.0799)	(0.0253)
Treat*(3rd Post Year)	-0.0218*	-0.0189	0.0308	0.0208	-0.0926***
	(0.0126)	(0.0162)	(0.0285)	(0.0746)	(0.0237)
Demographics	Yes	Yes	Yes	Yes	Yes
Year Dummies	Yes	Yes	Yes	Yes	Yes
Location	Yes	Yes	Yes	Yes	Yes
Firm Fixed Effects	Yes	Yes	Yes	Yes	Yes
Observations	10,851,860	10,851,860	10,851,860	10,851,860	10,851,860

Clustered (at firm level) standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. GLM Models estimated with a Gamma distributional assumption and log-link. Demographics include gender, age, age squared, six level family type, median household income (zip), % unemployed (zip), % college degree (zip), % high school degree (zip), % Hispanic (zip) % Black (zip), and % White (zip). Location controls include full interactions between 9 census region dummies and a dummy for being in an MSA.