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Health Insurance Policy and the Social Security Disability Insurance Population

Brett Alfrey

ABSTRACT

HEALTH INSURANCE POLICY AND THE SOCIAL SECURITY DISABILITY INSURANCE POPULATION

By

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Major Department: Economics

Individuals receiving benefits from the Social Security Disability Insurance (SSDI) program have both increased health needs but potentially more limited health insurance options. Although SSDI beneficiaries qualify for Medicare after receiving 24 months worth of benefit payments, their ability to procure health insurance during the waiting period is questionable, and before the Medicare Part D expansion, their ability to acquire prescription drug insurance coverage after the waiting period was also questionable. I investigate the effects of health insurance policy on the health insurance access and outcomes for this understudied group.

In the first chapter, I investigate the effect of the Affordable Care Act on SSDI beneficiaries in the Medicare waiting period. An open question is whether SSDI beneficiaries have adequate health insurance options during the waiting period. In this study, I use difference-in-difference-in-differences estimation and data from the American Community Survey to estimate the effects of the ACA on this group. For SSDI beneficiaries in the waiting period, I estimate that the policy increased health insurance coverage by 8.3 percentage points. In Medicaid expansion states, coverage increased 12.0 percentage points, and in non-expansion states, coverage increased 3.5 percentage points. The large health insurance gains suggest that

the ACA improved health insurance access during the Medicare waiting period.

In the second chapter, I investigate the effect of the Medicare Part D expansion on the prescription drug coverage, utilization, and expenditures of Medicare-eligible SSDI beneficiaries. I use difference-in-differences estimation and data from the Medical Expenditure Panel Survey (MEPS). I estimate large gains in prescription drug coverage and large decreases in annual out-of-pocket prescription drug expenditure. Additionally, the estimates suggest modest substitution away from private prescription drug coverage and little decrease in annual private insurance prescription drug expenditure. The estimates suggest large welfare gains from the policy.

In the third chapter, I investigate additional effects of the Medicare Part D expansion on Medicare-eligible SSDI beneficiaries. I look at the heterogeneous effects of the policy across this group based on demographic characteristics in the MEPS data. Additionally, I investigate how the policy affected self-reported health status. I use the same data set and a similar empirical strategy as Chapter 2. I estimate that the policy increased drug coverage more for: older individuals relative to younger individuals; individuals with some college education relative to individuals without college education; men relative to women; and married individuals relative to unmarried individuals. This led to larger decreases in out-of-pocket drug expenditure for the same subgroups. The estimates also suggest improvements in both perceived health status and perceived mental health status. I also evaluate the effects on non-prescription drug outcomes as well as prescription drugs prices, but the results are difficult to draw inference from.

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ACCEPTANCE

This dissertation was prepared under the direction of the candidate's Dissertation Committee. It has been approved and accepted by all members of that committee, and it has been accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy in Economics in the Andrew Young School of Policy Studies of Georgia State University.

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Dedication

To my family.

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CHAPTER 1: How Did the Affordable Care Act Affect Social Security Disability Insurance Beneficiaries Waiting for Medicare? A Look at Changes in Health Insurance Coverage

1.1 Introduction

Health insurance access is an ongoing concern for United States policymakers. One particular group of concern is Social Security Disability Insurance (SSDI) beneficiaries. SSDI is a federal insurance program that provides United States workers with cash payments in the event of a long-term disability. For working-age adults in the United States, the primary source of health insurance coverage is from an employer (Keisler-Starkey & Bunch, 2022). Individuals who can no longer work because of a disability, then, may lose their main source of health insurance coverage once they become disabled.[1] Before the Patient Protection and Affordable Care Act (ACA), these same individuals could be denied individual health insurance coverage because of pre-existing conditions exclusions.

To protect against the loss of health insurance, SSDI beneficiaries have access to Medicare benefits after an initial 24-month waiting period. An open question is whether SSDI beneficiaries have adequate health insurance access during the waiting period. Policymakers have expressed concern, with some lawmakers calling for the elimination of the Medicare waiting period: recently proposed legislation includes the Ending the Medicare Disability Waiting Period Act of 2005 (2005) and the Stop the Wait Act (2019).

The ACA ushered in significant changes to the United States health insurance landscape. Significant changes included the Medicaid expansion, the employer mandate, the individual mandate, and the overhaul of the individual health insurance markets. Most of these changes

[1] SSDI beneficiaries can continue employer-based health insurance coverage for up to 29 months after their date of disability (as a part of COBRA coverage), but the employer can charge the former employee up to 102 percent of the health insurance premium.

took effect in 2014. The ACA was intended to significantly increase health insurance coverage for the United States population (Gruber, 2011).

Using difference-in-difference-in-differences estimation and data from the American Community Survey, I estimate the effect of the ACA coverage expansions on the health insurance coverage of SSDI beneficiaries in the Medicare waiting period. I utilize differences in Medicaid expansion status by state, the 2012-2013 uninsured rate among non-Medicare-eligible SSDI beneficiaries by state, and years before and after the policy change. I estimate that, at the mean 2012-2013 uninsured rate, the policy increased health insurance coverage by 8.3 percentage points. In Medicaid expansion states, coverage increased 12.0 percentage points, and in non-expansion states, coverage increased 3.5 percentage points.

Little research has been done on the noted outcomes; this study attempts to fill some of that gap. With this study, policymakers will have a better understanding of whether SSDI beneficiaries have sufficient health insurance coverage during the waiting period or whether additional policies should be considered.

The rest of the paper is organized as follows. In Section 1.2, I give a background on the Medicare waiting period and health insurance options during the waiting period. In Section 1.3, I discuss relevant literature. In Section 1.4, I discuss the data used in the study. In Section 1.5, I discuss the methodology used in the study. In Section 1.6, I present the results from the empirical model. In Section 1.7, I discuss the results from the empirical model and conclude the paper.

1.2 Background

Medicare, created in 1965, was extended to SSDI beneficiaries in 1972 (Committee on Finance, 1972).[2] From the beginning, SSDI beneficiaries have had a 24-month waiting period

[2] The legislation extending Medicare coverage to SSDI beneficiaries was enacted in 1972. For qualifying individuals, coverage began July 1, 1973.

before receiving Medicare coverage.[3] In developing the legislation, four reasons were given for creating the 24-month waiting period: to keep down Medicare costs; beneficiaries may already have private health insurance available during the waiting period; to avoid administrative issues when disability awards are delayed by the appellate process; and to only give Medicare benefits to individuals whose disability has "proven to be severe and long lasting."[4]

While waiting for Medicare coverage, SSDI beneficiaries must access health insurance from other sources. Prior to the ACA, non-Medicare-eligible SSDI beneficiaries had a patchwork of options: Medicaid; health insurance through a spouse or domestic partner's employer; or continuing employer-sponsored coverage after leaving an employer (commonly called "COBRA coverage").[5] Some SSDI beneficiaries would not have had access to any of these options: Medicaid required having low enough income; not all SSDI beneficiaries would have had a spouse or domestic partner who also had available health insurance coverage; and not all SSDI beneficiaries would have had employer-sponsored health insurance coverage prior to starting SSDI. Prior to the ACA, individual health insurance markets were not an option for many SSDI beneficiaries. Many of the state individual health insurance markets allowed insurers to deny coverage for pre-existing health conditions or set premiums based on individual health status.[6]

[3] In addition to a 24-month waiting period, there is a 5-month waiting period from the onset of disability before entitlement to SSDI benefits. For SSDI beneficiaries, therefore, there is a 29-month waiting period from the onset of disability until the receipt of Medicare benefits.
[4] The original quote from Committee on Finance (1972, p. 178) is "Such an approach would help to keep program costs within reasonable bounds, avoid overlapping private health insurance protection, particularly in those cases where a disabled worker may continue his membership in a group insurance plan for a period of time following the onset of his disability, and minimize certain administrative problems that might otherwise arise in cases in which entitlement to disability benefits is not determined until some time after application is made because of delays due to the appellate process. Moreover, this approach would provide assurance that the protection will be available to those whose disabilities have proven to be severe and long lasting."
[5] For COBRA coverage, the employer can charge the individual up to 102 percent of the total premium. SSDI beneficiaries can keep this coverage for the entirety of the Medicare waiting period.
[6] In 2013, five states - Maine, Massachusetts, New Jersey, New York, and Vermont – required all individually purchased policies to be guaranteed issued (i.e., insurers could not consider pre-existing conditions) and community rated (i.e., insurers could not set premiums based on individual health status) (Claxton et al., 2016).

The ACA ushered in significant health insurance reforms for the U.S. population. The ACA expanded Medicaid coverage to millions of Americans, though it was enacted in a piecemeal fashion dependent on states' choices. Although some SSDI beneficiaries had Medicaid coverage prior to the ACA, many stood to gain coverage because of the increased income limit (Wagner, 2015); the average income limit for disabled Medicaid beneficiaries in 2008 was 87 percent of the federal poverty level (FPL), and the Medicaid expansion raised the income limit for all adults to 138 percent FPL. A second reform was the employer mandate, which required large employers to offer health insurance to all full-time employees. A third change was to individual health insurance markets: the ACA ended the practice of pre-existing condition exclusions, and the ACA also ended the ability of insurers to set premiums based on health status. Premium subsidies and cost-sharing subsidies for low-income enrollees were also new features of individual markets. Each of these changes brought on by the ACA could have increased health insurance access for SSDI beneficiaries waiting for Medicare. (For a figure summarizing the change in insurance options for this group, see Figure A1.)

The Medicaid expansion was ultimately ruled unconstitutional by the U.S. Supreme Court, and states were not obligated to expand Medicaid coverage because of the ACA. The Supreme Court, however, allowed states to expand and still receive federal funding for the expanded population. Regarding states that adopted the Medicaid expansion, most states adopted the expansion starting in 2014 while some states adopted it in later years (KFF, 2022).[7]

In 2013, the year before much of the ACA took effect, approximately 1.5 million SSDI beneficiaries were in the Medicare waiting period (Social Security Administration, 2015). Additionally, SSDI beneficiaries in the waiting period have significantly higher health care cost

[7] I discuss the staggered adoption of Medicaid expansions in the Data section (Section 1.4) and the Discussion section (Section 1.7).

relative to other working-age adults: $10,746 in average medical care spending for SSDI beneficiaries in the waiting period versus $3,750 for working-age individuals (Author's calculations using 2013 data from the Medical Expenditure Panel Survey). Both the number of beneficiaries and the amount of their health care spending show the potential welfare gain of a health insurance reform for this group.

1.3 Literature Review

Many studies have examined the ACA's effect on the overall U.S. population. The studies have examined changes in health insurance, health care spending, and health care utilization (see Gruber and Sommers (2019)). The studies find, generally, that the law increased health insurance coverage and utilization with reductions in out-of-pocket spending.

Little research has been done to understand how non-Medicare-eligible SSDI beneficiaries were affected by the ACA. I find no studies in the literature. This study would provide the first results about how the ACA affected this group.

Some studies look at the effect of the ACA on persons with disabilities generally. These papers find that, for persons with disabilities, the ACA Medicaid expansion increased health insurance coverage (Creedon et al., 2022; Dong et al., 2022; Hill & Hyde, 2020; Hill et al., 2021; Stimpson et al., 2019) and decreased out-of-pocket medical expenditure (Creedon et al., 2022). The studies find mixed results on changes in utilization (Creedon et al., 2022; Dong et al., 2022; Hill & Hyde, 2020; Hill et al., 2021). Hill et al. (2021) also notes increased health insurance coverage in both Medicaid expansion and non-expansion states, but the authors do not separately attribute effects of the Medicaid expansion from the other ACA reforms.

1.4 Data

The primary data source for the study is the American Community Survey (ACS). Additionally, I use state-level unemployment rates by year (U.S. Bureau of Labor Statistics, 2021) as a control variable for the analysis.

For the study, I focus on the years 2011-2019. I start in the year 2011 to avoid confounding from the dependent coverage mandate. The dependent coverage mandate required employer-provided health insurance to cover dependents up to age 26, and the mandate went into effect in 2010. Additionally, by starting in the year 2011, I can avoid some of the lingering effects of the Great Recession (which officially ended in 2009). I end the data series in 2019 to avoid any effects from the onset of the Coronavirus disease 2019 (COVID-19) pandemic, which significantly affected U.S. labor markets and may have also caused data collection issues for the 2020 round of the ACS (Daily et al., 2021).

1.4.1 American Community Survey

I use the ACS from the Integrated Public Use Microdata Series (IPUMS-ACS) data set (Ruggles et al., 2022). The ACS is a nationally representative survey of the United States that collects and produces information on social, economic, and demographic characteristics. The survey is conducted every year by the U.S. Census Bureau, and it surveys approximately one percent of the U.S. population. As the survey has a large sample size, contains state-level identifiers, and has information on health insurance coverage, it serves as a good source for this study. Regarding the IPUMS-ACS data set, it is a highly regarded compilation of all the ACS data into one source, so I choose to use the IPUMS-ACS data set.

I use the health insurance coverage variables from the IPUMS-ACS as the outcomes of interest. The ACS asks participants about health insurance coverage at the time of the interview.

The survey asks “Is this person CURRENTLY covered by any of the following types of health insurance or health coverage plans?”, and then asks participants to select “Yes” or “No” for the following types of coverage: insurance through a current or former employer or union, insurance purchased directly from an insurance company, Medicare, Medicaid, TRICARE, VA health care, Indian Health Service, or other types of health insurance plans (which are then classified into one of the seven types). The IPUMS-ACS then further classifies these types of coverage into public health insurance coverage and private health insurance coverage. Public health insurance coverage includes Medicare, Medicaid, and VA health care. Private health insurance coverage includes insurance through a current or former employer or union, insurance purchased directly from an insurance company, and TRICARE. Lastly, the IPUMS-ACS has an “any” coverage variable, which consists of coverage from either the public sources or the private sources.[8] I create indicator variables for each of the insurance types. These variables serve as the outcomes of interest.

To identify SSDI beneficiaries in the ACS, I use survey responses about whether the individual receives Social Security income. The ACS surveys individuals about their income in the past 12 months and then asks them to classify it into eight different sources. One of the sources it asks about is “Social Security or Railroad Retirement.” The ACS does not ask whether an individual is receiving Social Security income because of SSDI, though. To identify SSDI beneficiaries for the sample, then, I only include individuals ages 20-59 who report positive Social Security income. Individuals aged 60 and older can receive Social Security income related to survivor benefits if they are not disabled, and children can receive survivor

[8] The IPUMS-ACS does not count Indian Health Service policies as health insurance coverage. The U.S. Census Bureau does not consider individuals to have health insurance coverage if their only coverage is from the Indian Health Service, as Indian Health Service policies are not always comprehensive.

benefits up to age 19 (Social Security Administration, 2019). Individuals under age 64 can receive SSDI benefits. By keeping individuals who report positive Social Security income and are between the ages 20-59, I avoid including individuals who could be receiving other Social Security benefits. Finally, I exclude individuals who report Medicare coverage as I only want individuals in the Medicare waiting period.

As a part of the identification strategy, I require state-level identifiers. State-level identifiers allow me to determine which individuals were in states that expanded Medicaid, and they can also be used to determine the uninsurance rate by state for non-Medicare-eligible SSDI beneficiaries. Regarding the ACA Medicaid expansions, I consider states that expanded their Medicaid program by 2014 as a part of the "treatment" group; 26 states plus Washington, DC expanded their Medicaid programs by 2014 (KFF, 2022).[9,10] I consider states that had not expanded their Medicaid program as of 2019 as a part of the "control" group, which included 17 states.[11] Seven states adopted the ACA Medicaid expansion between the years 2015-2019.[12] Because staggered policy adoption can lead to biased coefficient estimates when using difference-in-differences estimation (Goodman-Bacon, 2021), I exclude individuals from these seven states.[13]

[9] The 26 states (in addition to Washington, DC) that expanded were Arizona, Arkansas, California, Colorado, Connecticut, Delaware, Hawaii, Illinois, Iowa, Kentucky, Maryland, Massachusetts, Minnesota, Nevada, New Jersey, New Mexico, New York, North Dakota, Ohio, Oregon, Rhode Island, Vermont, Washington, West Virginia, Michigan, and New Hampshire.

[10] Six states partially or fully expanded their Medicaid program between 2010 and 2013 (Sommers et al., 2013). The six states (California, Connecticut, District of Columbia, Minnesota, New Jersey, and Washington) used either an ACA option that allowed expansion at the state's current Medicaid reimbursement rate or a Section 1115 waiver (KFF, 2012). Two other states (Colorado and Missouri) had minor early expansions, where the Colorado expansion was capped at 10,000 individuals and the Missouri expansion was only for one county.

[11] The 17 states that did not expand as of 2019 were Alabama, Florida, Georgia, Idaho, Kansas, Mississippi, Missouri, Nebraska, North Carolina, Oklahoma, South Carolina, South Dakota, Tennessee, Texas, Utah, Wisconsin, and Wyoming.

[12] The seven states, along with their date of expansion, were Pennsylvania (1/1/2015), Indiana (2/1/2015), Alaska (9/1/2015), Montana (1/1/2016), Louisiana (7/1/2016), Virginia (1/1/2019), and Maine (1/10/2019).

[13] As discussed in Section 1.5, I use a difference-in-difference-in-differences model where one of the differences is a pre-period continuous measure of a variable of interest (or a dose-response approach). I am not aware of an

I use state-level uninsurance rates in 2012-2013 as another source of variation. Some papers in the literature use substate uninsurance rates as a source of variation (Courtemanche, Friedson, et al., 2019; Courtemanche et al., 2017; Decker et al., 2023). Given I use a similar empirical strategy as these papers, it might make sense to also use substate uninsurance rates. The problem, however, is that I am using a much smaller sample for calculating the uninsurance rates. This could result in poor estimates for the local area uninsurance rates, which could lead to biased regression estimates. I choose, therefore, to use state-level uninsurance rates. Additionally, to improve the sample size for calculating each uninsurance rate, I use data from both 2012 and 2013 instead of just one year.

To control for differences in demographics across individuals, I use the following variables: age (indicator variables for age bands of 25-29, 30-34, 35-39, 40-44, 45-49, 50-54, and 55-59), race/ethnicity (indicator variables for Black non-Hispanic, Hispanic, and other non-White), and individual's sex (indicator variable if female). To control for differences in family composition, I use the following variables: marital status (indicator variables for widowed, divorced, separated, and never married) and number of own children in the household (indicator variables for 1 child, 2 children, 3 children, 4 children, 5+ children). Lastly, I use the following economic controls: educational attainment (indicator variables for GED or high school diploma, some college, and bachelors degree or higher) and state unemployment rates (from the U.S. Bureau of Labor Statistics).[14,15]

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estimator for developing unbiased estimates when using such an approach. None are listed in a recent review of the literature (Roth et al., 2023). The closest is the estimator from Borusyak et al. (2023), which can be extended to a difference-in-difference-in-differences model but not when trying to separately identify two effects (using two difference coefficients) from the model.

[14] For the indicator variables, the omitted group is ages 20-24, less than GED or high school diploma, married, White non-Hispanic, male, and 0 children.

[15] I do not include income as a control variable in the model. During the first year on the SSDI rolls, some beneficiaries can receive delayed earnings income based on past work (Liu & Stapleton, 2010). Additionally, the ACS asks respondents how much income they made in the past 12 months from the time of the survey; this means

1.4.2 Summary Statistics and Trend Graphs

Table 1 shows sample means and standard deviations for the outcomes of interest.[16] The table shows various splits based on time period, whether the state expanded Medicaid under the ACA, and whether a state's 2012-2013 uninsured rate was above or below the national median 2012-2013 uninsured rate. Columns (1) and (2) show the statistics for the full sample split between the pre-period (2011-2013) and the post-period (2014-2019). Columns (3)-(6) show the statistics for states that expanded Medicaid under the ACA. Columns (7)-(10) show statistics for states that did not expand their Medicaid program under the ACA.

The table suggests that all types of states experienced an increase in any insurance coverage after implementation of the ACA. The table also suggests that private and public coverage increased in all types of states (except for private coverage in Medicaid expansion states below the median baseline uninsured rates). The statistics suggest that a formal empirical strategy would be useful to estimate the ACA's effects.

To get an initial sense of the policy's year-to-year effects, I develop some trend graphs using the IPUMS-ACS data. Figures 1-3 show the changes in health insurance coverage rates over time. Figure 1 has three graphs for the three aggregate coverage categories: any coverage, public coverage, and private coverage. Figure 2 has two graphs for the two public coverage types: Medicaid coverage and VA health coverage.[17] Figure 3 has three graphs for the three private coverage types: employer/union coverage, individual insurance market coverage, and TRICARE coverage. All graphs are produced using the same scale so that they are more easily

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that beneficiaries might also report income they earned prior to SSDI benefit receipt. I am concerned this reported income does not accurately reflect a beneficiaries' financial state, so I do not include income as a control variable.

[16] Table A1 shows pre-period sample means and standard deviations for the various control variables.

[17] Medicare coverage is also a form of public coverage, but I do not produce a graph for Medicare coverage as I only include individuals in the sample who report not having Medicare coverage.

Table 1. Summary Statistics - Sample Means of Outcome Variables by Medicaid Expansion Status and 2012/2013 Uninsured Rate

Variable	Full sample		Medicaid expansion; at or above median baseline uninsured		Medicaid expansion; below median baseline uninsured	
	Pre-period (1)	Post-period (2)	Pre-period (3)	Post-period (4)	Pre-period (5)	Post-period (6)
Overall coverage						
Any insurance coverage	0.825	0.901	0.801	0.916	0.873	0.937
	(0.380)	(0.299)	(0.400)	(0.278)	(0.332)	(0.243)
Private coverage						
Any private	0.393	0.413	0.353	0.369	0.429	0.426
	(0.488)	(0.492)	(0.478)	(0.482)	(0.495)	(0.495)
Employer-union coverage	0.310	0.302	0.279	0.275	0.349	0.332
	(0.462)	(0.459)	(0.449)	(0.447)	(0.477)	(0.471)
Indiv. purchased directly	0.084	0.105	0.074	0.086	0.089	0.097
	(0.277)	(0.307)	(0.261)	(0.280)	(0.284)	(0.296)
TRICARE	0.023	0.027	0.021	0.027	0.015	0.017
	(0.150)	(0.162)	(0.145)	(0.163)	(0.123)	(0.128)
Public coverage						
Any public	0.499	0.571	0.514	0.625	0.512	0.593
	(0.500)	(0.495)	(0.500)	(0.484)	(0.500)	(0.491)
Medicaid	0.468	0.540	0.476	0.589	0.491	0.572
	(0.499)	(0.498)	(0.499)	(0.492)	(0.500)	(0.495)
VA	0.040	0.042	0.048	0.050	0.028	0.029
	(0.195)	(0.200)	(0.213)	(0.218)	(0.166)	(0.168)
Total sources						
Number of Sources	0.924	1.016	0.898	1.027	0.972	1.046
	(0.541)	(0.494)	(0.558)	(0.475)	(0.497)	(0.440)
Observations	57,681	104,667	11,440	20,894	22,094	40,800

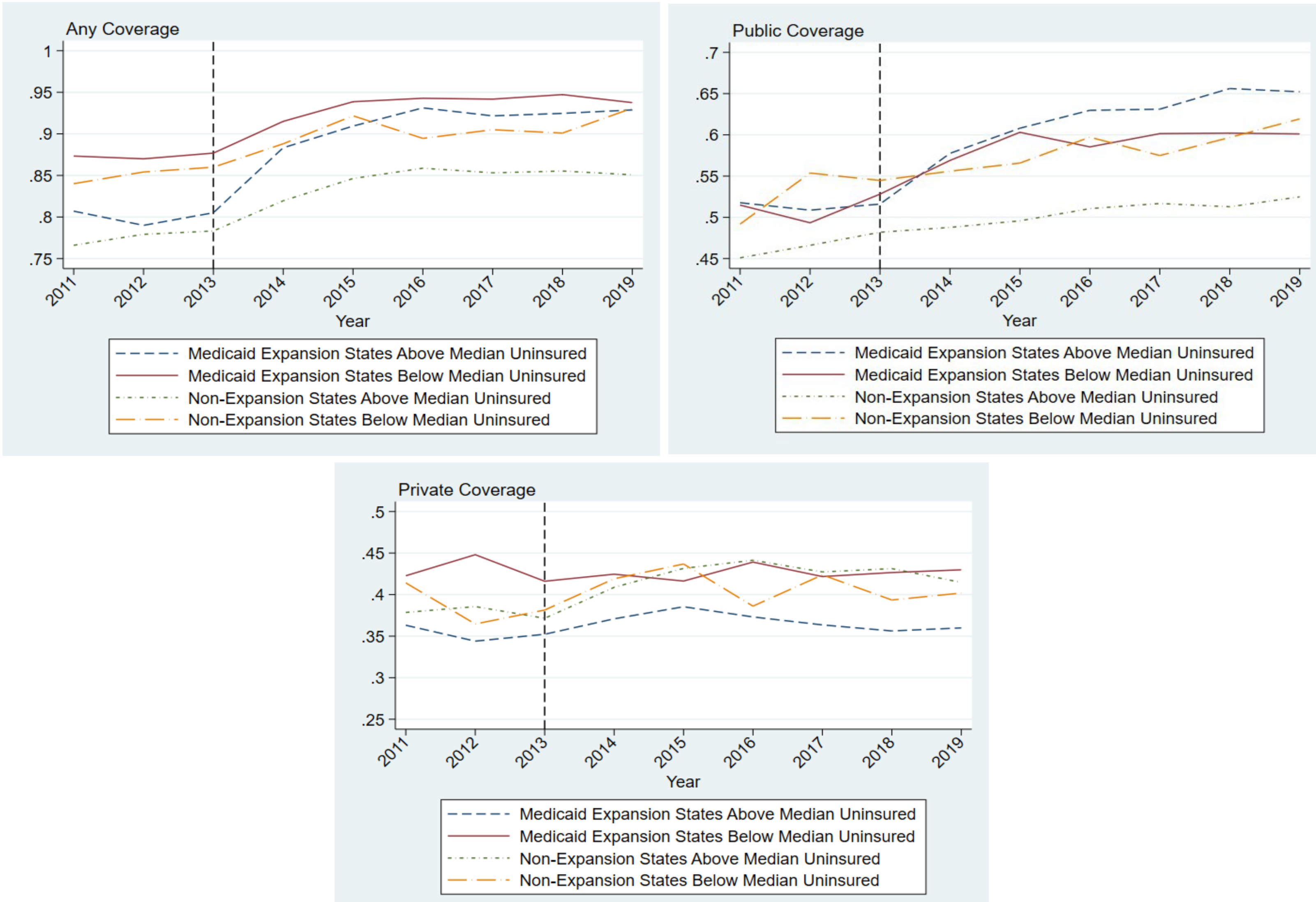
Notes: Data from the IPUMS-ACS for years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded. Standard deviations in parentheses.

Table 1. Summary Statistics - Sample Means of Outcome Variables by Medicaid Expansion Status and 2012/2013 Uninsured Rate (continued)

	Non-expansion; at or above median baseline uninsured		**Non-expansion; below median baseline uninsured**	
Variable	Pre-period (7)	Post-period (8)	Pre-period (9)	Post-period (10)
Overall coverage				
Any insurance coverage	0.777	0.848	0.855	0.915
	(0.416)	(0.359)	(0.352)	(0.279)
Private coverage				
Any private	0.377	0.422	0.403	0.424
	(0.485)	(0.494)	(0.491)	(0.494)
Employer-union coverage	0.286	0.282	0.316	0.312
	(0.452)	(0.450)	(0.465)	(0.463)
Indiv. purchased directly	0.084	0.126	0.085	0.106
	(0.277)	(0.332)	(0.279)	(0.308)
TRICARE	0.031	0.038	0.022	0.025
	(0.174)	(0.192)	(0.146)	(0.156)
Public coverage				
Any public	0.468	0.511	0.520	0.582
	(0.499)	(0.500)	(0.500)	(0.493)
Medicaid	0.430	0.473	0.488	0.549
	(0.495)	(0.499)	(0.500)	(0.498)
VA	0.047	0.051	0.042	0.043
	(0.212)	(0.221)	(0.201)	(0.203)
Total sources				
Number of Sources	0.878	0.971	0.952	1.035
	(0.579)	(0.558)	(0.514)	(0.476)
Observations	26,044	34,944	5,531	8,029

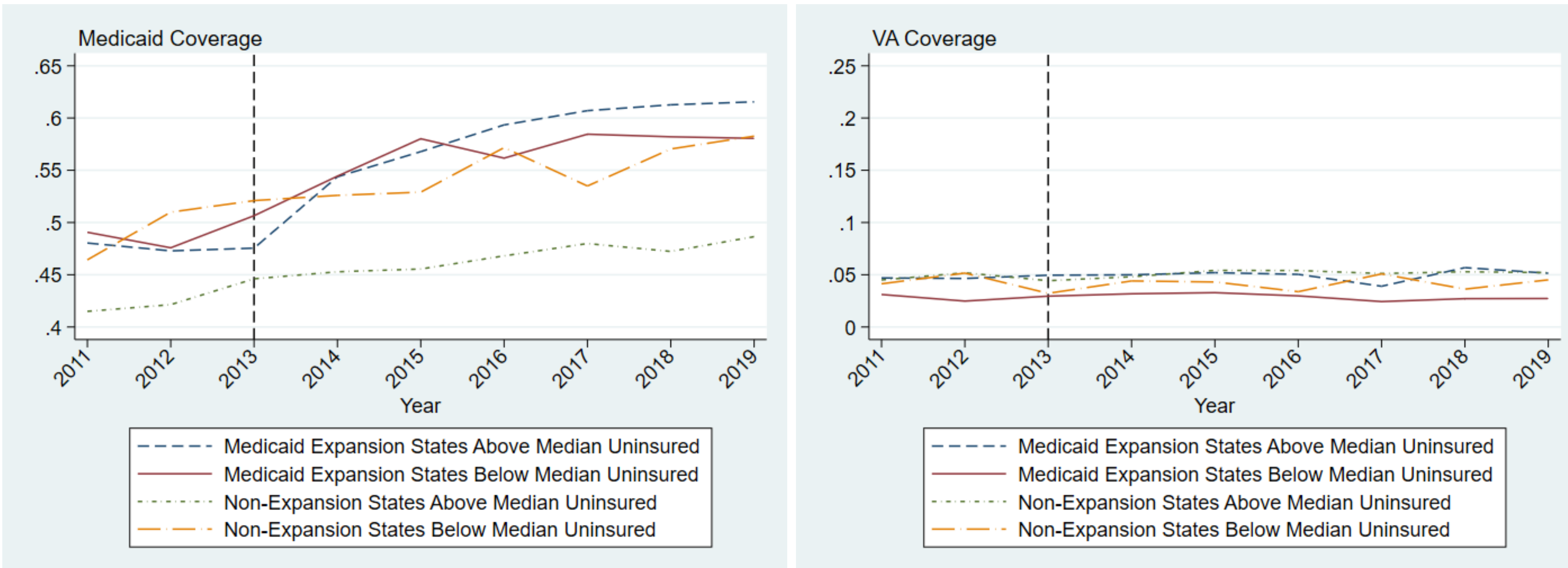
Notes: Data from the IPUMS-ACS for years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded. Standard deviations in parentheses.

Figure 1. Coverage Rates - By Aggregate Coverage Categories



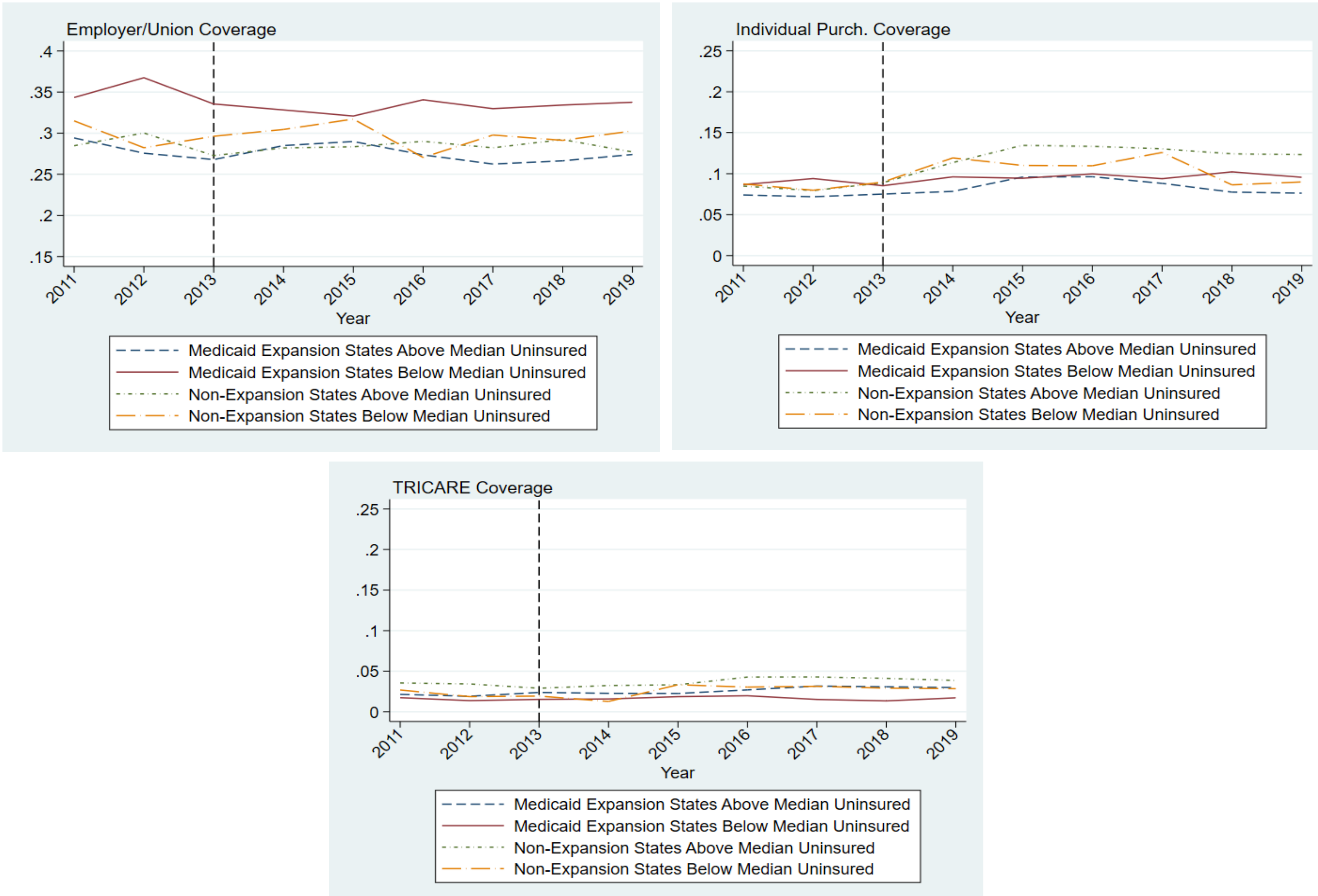
Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 2. Coverage Rates - By Public Coverage Type



Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 3. Coverage Rates - By Private Coverage Type



Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

comparable to one another.

The graph for any coverage in Figure 1 suggests that coverage increased during the first couple years after implementation of the ACA before leveling off after 2016. The four types of states experienced this trend on average, though the level of increase appears largest in expansion states that were above the median baseline uninsured rate. The graph for public coverage also shows increases in coverage across all types of states without the leveling off in the graph for any coverage. The graph for private coverage suggests changes mainly in states above the median baseline uninsured rate.

Regarding trends in the pre-period, no graph seems to show any concerning pre-reform trends. Some of the graphs are a bit noisy in the pre-period years, but I do not think it is anything of concern. A formal event study analysis is warranted to study pre-reform trends.

1.5 Empirical Strategy

1.5.1 Empirical Model

To estimate the effects of the ACA, I use a difference-in-difference-in-differences model. I follow similar methodological strategies as other studies on health insurance reform (Courtemanche, Friedson, et al., 2019; Courtemanche et al., 2017; Decker et al., 2023; Mazumder & Miller, 2016; Miller, 2012). The studies use geographical regions' uninsurance rate to identify the effect of an insurance reform on outcomes of interest. Some studies use additional variation (such as a Medicaid expansion) to further identify effects from a policy. In my study, the three differences are Medicaid expansion status by state, the 2012-2013 uninsured rate among non-Medicare-eligible SSDI beneficiaries by state, and years before and after the policy;

the identification strategy is adapted from Courtemanche et al. (2017).[18] The idea is that states with higher uninsured rates for non-Medicare-eligible SSDI beneficiaries will see a larger impact from the policy. This will help identify the effects separately for the Medicaid expansions and the other ACA components. For identifying the effects of the Medicaid expansions, the identifying assumption is: after 2013, differential changes in outcomes in high and low uninsured rate expansion states would have evolved similarly to differential changes in outcomes in high and low uninsured rate non-expansion states.[19] For identifying the effects of the other ACA components, the identifying assumption is: after 2013, changes in outcomes would not have varied differentially for high and low uninsured rate areas.

Based on the above comments, I specify the following model:

$$\begin{aligned} y_{ist} = \beta_0 + \ & \beta_1(MedicaidExp_s \times Post_t) \\ & + \beta_2\big(UninsuredRate_{s,2012/2013} \times Post_t\big) \\ & + \beta_3\big(MedicaidExp_s \times UninsuredRate_{s,2012/2013} \times Post_t\big) \\ & + \mathbf{X}'_{\boldsymbol{ist}}\gamma + \theta_s + \lambda_t + \varepsilon_{ist} \end{aligned} \tag{1.1}$$

where y_{ist} is the outcome of interest for individual i in year t in state s, $MedicaidExp_s$ is 1 if state s had expanded their Medicaid program by year 2014, $UninsuredRate_{s,2012/2013}$ is the uninsured rate in 2012-2013 for non-Medicare-eligible SSDI beneficiaries in state s, $Post_t$ is 1 if year t is greater than 2013, $\mathbf{X}_{ist}$ is a vector of controls (demographics and state unemployment rates), θ_s represents state fixed effects, λ_t represents year fixed effects, and ε_{ist} is the error

[18] An alternative approach could incorporate income as a difference in the model. This may be appealing as the policy should have had a larger effect for 1.) individuals newly eligible for Medicaid based on the increased income limit, and 2.) individuals eligible for subsidies in the individual health insurance markets. I am concerned, though, about income being endogenous. Individuals or their spouses may alter their level of work to qualify for Medicaid or the subsidies. Additionally, as discussed in Section 1.4, I am concerned about using an income variable for new SSDI beneficiaries.

[19] Presumably, states were not expanding their Medicaid programs specifically to help SSDI waiting period beneficiaries, which gives me some confidence regarding the identifying assumption.

term.[20] I use person-level sampling weights from the IPUMS-ACS, and I cluster standard errors at the state-level. With the specified empirical model, the coefficients of interest are β_2 and β_3. The implied effect of the ACA Medicaid expansion only is $\beta_3 \times UninsuredRate_{s,2012/2013}$. I interpret this as the effect of the Medicaid expansion in only the states that expanded. The implied effect of the other ACA components is $\beta_2 \times UninsuredRate_{s,2012/2013}$. I interpret this as the effect of the other ACA components in all states. The combined implied effect, thus, is the addition of the two, or $(\beta_2 + \beta_3) \times UninsuredRate_{s,2012/2013}$. I interpret this as the effect of both the Medicaid expansion and the other ACA components in only the states that expanded their Medicaid program. When estimating the implied effects, I use the average uninsured rate for the sample in 2012-2013, which is $\overline{UninsuredRate}_{s,2012/2013} = 17.3$ percent. I also estimate the heterogeneous effects of the policy across various demographic groups. I use the uninsured rate for each specific subsample for the years 2012-2013. The uninsured rates for the subsamples range from 15.2 percent to 19.2 percent.

1.5.2 Event Study

To understand the post-2013 dynamics of the policy and to indirectly test the parallel trends assumption, I specify an event study model based on equation (1.1). The model is as follows:

$$
\begin{aligned}
y_{ist} = \alpha_0 &+ \sum_{\substack{k=2011 \\ k\neq 2013}}^{2019} \beta_k (MedicaidExp_s \times \mathbb{1}(t=k)) \\
&+ \sum_{\substack{k=2011 \\ k\neq 2013}}^{2019} \zeta_k \big(UninsuredRate_{s,2012/2013} \times \mathbb{1}(t=k)\big)
\end{aligned}
\tag{1.2}
$$

[20] $MedicaidExp_s$, $UninsuredRate_{s,2012/2013}$, and $MedicaidExp_s \times UninsuredRate_{s,2012/2013}$ are not separately included in the equation because they are perfectly collinear with the state effects. $Post_t$ is not separately included in the equation because it is perfectly collinear with the year fixed effects.

$$+\sum_{\substack{k=2011\\k\neq 2013}}^{2019} \eta_k\big(MedicaidExp_s \times UninsuredRate_{s,2012/2013} \times \mathbb{1}(t=k)\big)$$

$$+\mathbf{X}'_{ist}\delta + \theta_s + \lambda_t + \upsilon_{ist}$$

where $\mathbb{1}(t = k)$ is an indicator function for whether the year of the observation is equal to the year being evaluated. The other variables are defined the same as in equation (1.1). The year 2013 is the reference year, so it is excluded from the event study. I cluster standard errors at the state-level.

For the event study model, the following pre-period variables are of interest: ζ_{2011}, ζ_{2012}, η_{2011}, and η_{2012}. The associated coefficient estimates can indirectly test the parallel trends assumption; if the coefficient estimates are not statistically significant, this can provide suggestive evidence supporting the parallel trends assumption. The following post-period variables are of interest: ζ_{2014}, ζ_{2015}, ζ_{2016}, ζ_{2017}, ζ_{2018}, ζ_{2019}, η_{2014}, η_{2015}, η_{2016}, η_{2017}, η_{2018}, and η_{2019}. The associated coefficient estimates help us understand the year-to-year effects of the policy. I also estimate implied effects using the coefficients, similar to what is described in Subsection 1.5.1. I use the average uninsured rate for the sample in 2012-2013, which is $\overline{UninsuredRate}_{s,2012/2013} = 17.3$ percent.

1.6 Results

Table 2 reports estimates based on equation (1.1); the table also reports implied effects based on the model estimates and the average 2012-2013 uninsured rate.[21] The top part of the table shows the coefficient estimates from the model, and the bottom part of the table shows the implied effects. The "Medicaid expansion" row in the bottom part of the table is the estimated

[21] Standard errors for the implied effects are calculated using the "lincom" command in Stata. Other papers in the literature have used this approach.

Table 2. OLS Estimates and Implied Effects of the Affordable Care Act Introduction on Outcomes of Interest

Dependent Variable:	Any Covg	Private Coverage				Public Coverage		
	Any coverage	Any private	Employer-union coverage	Indiv. purch. directly	TRICARE	Any public	Medicaid	VA
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Coefficient estimates of interest								
$MedicaidExp_s \times$	0.489***	-0.035	0.064	-0.064	0.049	0.543***	0.525***	0.003
$UninsuredRate_{s,2012/2013} \times$	(0.096)	(0.142)	(0.145)	(0.091)	(0.052)	(0.171)	(0.178)	(0.038)
$Post_t$								
$UninsuredRate_{s,2012/2013} \times$	0.202**	0.263**	0.091	0.142*	-0.022	-0.115	-0.069	-0.015
$Post_t$	(0.089)	(0.116)	(0.117)	(0.078)	(0.044)	(0.150)	(0.156)	(0.026)
Implied effects of ACA at mean 2012/2013 uninsured rate								
Medicaid	0.085***	-0.006	0.011	-0.011	0.008	0.094***	0.091***	0.000
expansion	(0.017)	(0.025)	(0.025)	(0.016)	(0.009)	(0.030)	(0.031)	(0.007)
ACA without	0.035**	0.046**	0.016	0.025*	-0.004	-0.020	-0.012	-0.003
Medicaid exp.	(0.015)	(0.020)	(0.020)	(0.014)	(0.008)	(0.026)	(0.027)	(0.004)
Full ACA	0.120***	0.040***	0.027*	0.013*	0.005	0.074***	0.079***	-0.002
with Medicaid exp.	(0.006)	(0.014)	(0.014)	(0.008)	(0.005)	(0.013)	(0.014)	(0.005)
Observations	162,348	162,348	162,348	162,348	162,348	162,348	162,348	162,348

Notes: OLS estimates and implied effects for health insurance coverage. Data from the IPUMS-ACS for years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded. Underlying models include year fixed effects, state fixed effects, and all controls. For coefficient estimates, standard errors clustered at state-level are shown in parentheses. For implied effects, standard errors calculated using coefficient estimates, average 2012/2013 uninsured rate, and a linear combination of these parameters.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

effect of the Medicaid expansion in states that expanded Medicaid. The "ACA without Medicaid exp." row is the estimated effect of the other ACA components in all states. The "Full ACA with Medicaid exp." row adds the estimates from the other two rows to get a comprehensive estimate for the states that expanded Medicaid.

Looking at the implied effects, column (1) suggests that the Medicaid expansions increased health insurance coverage by 8.5 percentage points in expansion states (which comes from the "Medicaid expansion" row). Column (1) also suggests that the non-Medicaid ACA components increased health insurance coverage in expansion and non-expansion states by 3.5 percentage points (which comes from the "ACA without Medicaid exp." row). Lastly, the estimates suggest that the ACA altogether increased health insurance coverage in Medicaid expansion states by 12.0 percentage points (which comes from the "Full ACA with Medicaid exp." row). The "Full ACA with Medicaid expansion" estimate and the "Medicaid expansion" estimate are statistically significant at the 1 percent level, and the "ACA without Medicaid exp." estimate is statistically significant at the 5 percent level.

Looking at columns (2)-(8), the estimates suggest that Medicaid coverage increased in expansion states by 7.9 percentage points (which comes from the "Full ACA with Medicaid exp." row). Based on the estimates, the expansion itself increased Medicaid coverage by 9.1 percentage points and the other ACA components decreased Medicaid coverage by 1.2 percentage points (though the latter estimate is not statistically significant at the 10 percent level). Column (4), however, suggests that the Medicaid expansion might also have crowded out some individual market coverage (which decreased 1.1 percentage points in expansion states), though the coefficient estimate is not statistically significant. Because the main effects to public coverage seem driven by Medicaid coverage, I focus on Medicaid coverage throughout the rest of the study and do not examine either any public coverage or VA coverage.

Turning to the other ACA reforms, we notice that the main effects were increases in employer-based coverage and individually purchased coverage. In Medicaid expansion states, the larger increase was in employer-based coverage (which increased 2.7 percentage points). In non-expansion states, the larger increase was in individually purchased coverage (which increased by 2.5 percentage points). Both estimates are statistically significant at the 10 percent level. Because I estimate small and statistically insignificant effects for TRICARE coverage, I do not examine TRICARE coverage in the rest of the study.

1.6.1 Event Studies

I estimate the event study model specified in equation (1.2). Implied effects are reported in Table 3 and are plotted in Figures 4-8. The figures show implied effects along with 95 percent confidence intervals, and each figure shows estimates for the Medicaid expansion, the other ACA components, and the full ACA effect. Starting with the pre-reform trends, none of the pre-2013 implied effects are statistically significant at the 5 percent level. This gives me some confidence that the parallel trends assumption holds and that the results can be interpreted causally.

Turning to the post-reform trends, Figure 4 shows event study plots when the outcome is any coverage. For the "Full ACA Effect" graph, the post-period estimates suggest a large increase in coverage in 2014 followed by a steady increase through 2016. The point estimates decrease slightly from 2017 through 2019. The "Other ACA Effect" graph suggests small increases in coverage from 2014 through 2015 followed by a large increase in 2016. The point estimates then decrease slightly in 2017 and 2018 before becoming negative in 2019.

Table 3. Event Study Estimates - Implied Effects (*Base year 2013*)

	Any coverage	Any private coverage	Employer – union coverage	Indiv. purch. directly	Medicaid coverage
	(1)	(2)	(3)	(4)	(5)
Medicaid expansion (2011)	0.030 (0.031)	0.056 (0.034)	0.053 (0.039)	0.014 (0.030)	0.010 (0.034)
Medicaid expansion (2012)	0.019 (0.034)	-0.053 (0.040)	-0.049 (0.036)	-0.026 (0.029)	0.049 (0.040)
Medicaid expansion (2014)	0.093** (0.041)	-0.011 (0.033)	0.016 (0.038)	-0.006 (0.026)	0.114** (0.043)
Medicaid expansion (2015)	0.107*** (0.031)	0.012 (0.061)	-0.004 (0.044)	0.020 (0.043)	0.096* (0.050)
Medicaid expansion (2016)	0.087*** (0.031)	-0.042 (0.048)	-0.002 (0.042)	-0.029 (0.034)	0.139** (0.057)
Medicaid expansion (2017)	0.093*** (0.030)	0.003 (0.040)	0.012 (0.042)	0.002 (0.032)	0.091** (0.040)
Medicaid expansion (2018)	0.091*** (0.028)	-0.010 (0.039)	-0.012 (0.042)	-0.034 (0.036)	0.107** (0.042)
Medicaid expansion (2019)	0.143*** (0.029)	0.009 (0.039)	0.058 (0.038)	-0.050* (0.026)	0.127** (0.050)
ACA w/o Medicaid expansion (2011)	-0.001 (0.024)	-0.021 (0.022)	0.002 (0.028)	-0.016 (0.028)	0.018 (0.026)
ACA w/o Medicaid expansion (2012)	-0.029 (0.026)	0.043 (0.034)	0.059* (0.032)	0.010 (0.027)	-0.054* (0.029)
ACA w/o Medicaid expansion (2014)	0.002 (0.035)	0.031 (0.021)	0.024 (0.028)	0.000 (0.023)	-0.023 (0.038)
ACA w/o Medicaid expansion (2015)	0.014 (0.021)	0.046 (0.051)	0.058** (0.023)	0.009 (0.042)	-0.024 (0.045)

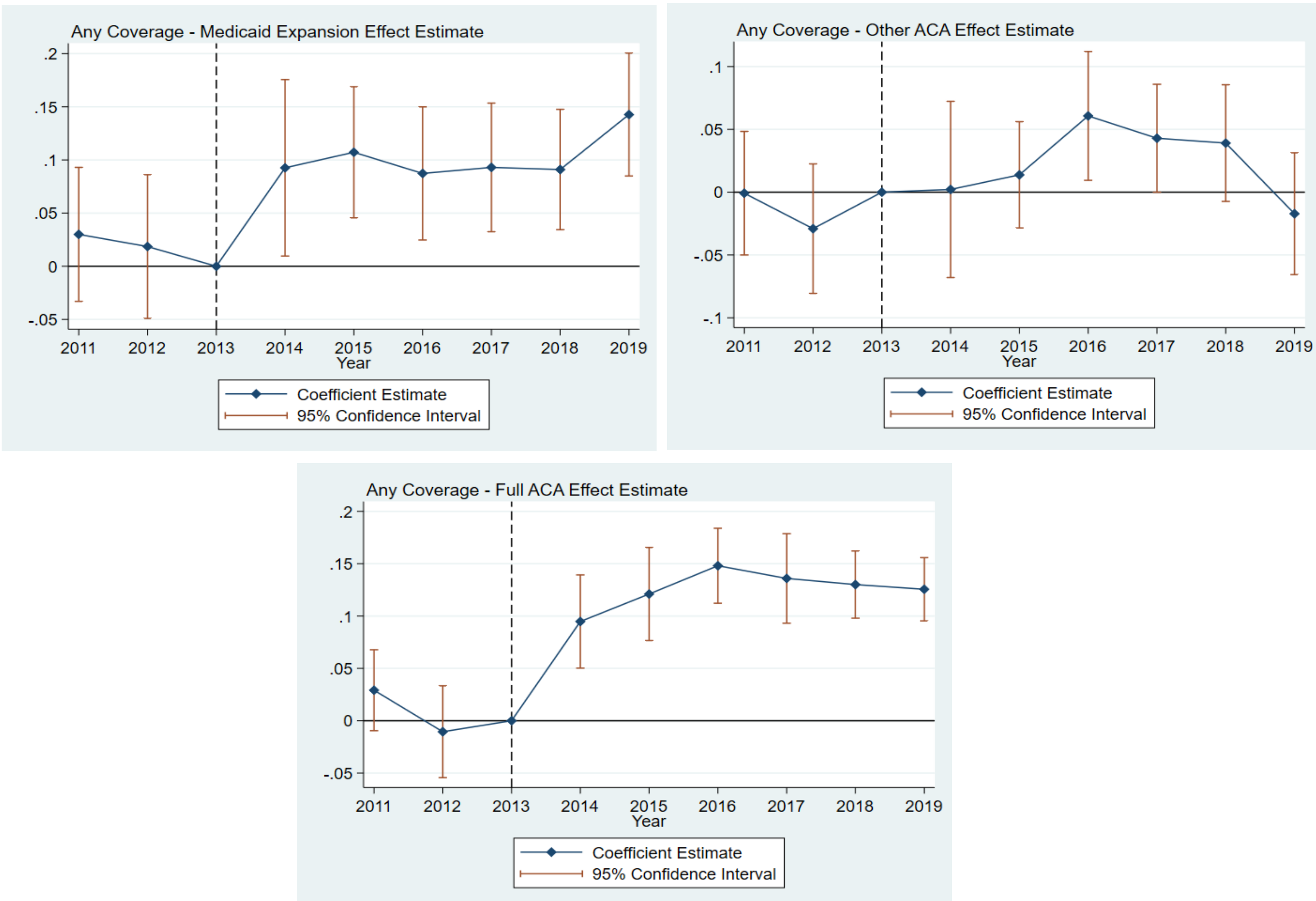
Table 3. Event Study Estimates - Implied Effects (*Base year 2013*) (continued)

ACA w/o Medicaid expansion (2016)	0.061**	0.091**	0.045	0.046	-0.032
	(0.025)	(0.039)	(0.035)	(0.031)	(0.052)
ACA w/o Medicaid expansion (2017)	0.043*	0.051*	0.028	0.008	0.004
	(0.021)	(0.028)	(0.020)	(0.027)	(0.033)
ACA w/o Medicaid expansion (2018)	0.039*	0.065**	0.058*	0.034	-0.022
	(0.023)	(0.029)	(0.033)	(0.033)	(0.034)
ACA w/o Medicaid expansion (2019)	-0.017	0.039	0.008	0.043*	-0.061
	(0.024)	(0.025)	(0.026)	(0.022)	(0.040)
Full ACA (2011)	0.029	0.036	0.055*	-0.001	0.028
	(0.019)	(0.026)	(0.028)	(0.011)	(0.021)
Full ACA (2012)	-0.010	-0.011	0.011	-0.016	-0.005
	(0.022)	(0.022)	(0.018)	(0.012)	(0.028)
Full ACA (2014)	0.095***	0.020	0.040	-0.006	0.091***
	(0.022)	(0.026)	(0.026)	(0.012)	(0.021)
Full ACA (2015)	0.121***	0.058*	0.053	0.029**	0.072***
	(0.022)	(0.032)	(0.038)	(0.012)	(0.022)
Full ACA (2016)	0.148***	0.049*	0.044*	0.017	0.107***
	(0.018)	(0.029)	(0.023)	(0.015)	(0.023)
Full ACA (2017)	0.136***	0.054*	0.041	0.010	0.095***
	(0.021)	(0.028)	(0.036)	(0.018)	(0.021)
Full ACA (2018)	0.130***	0.054**	0.046*	0.000	0.085***
	(0.016)	(0.027)	(0.026)	(0.014)	(0.024)
Full ACA (2019)	0.126***	0.048	0.066**	-0.007	0.065**
	(0.015)	(0.030)	(0.028)	(0.013)	(0.028)
Observations	162,348	162,348	162,348	162,348	162,348

Notes: Implied effects reported. Developed using linear combination of coefficient estimates and average uninsured rate. Data from the ACS-IPUMS for years 2011- 2019. Base year is 2013. Includes SSDI population between ages 20-59 without Medicare coverage. States that expanded Medicaid between 2015-2019 are excluded. Underlying models include year fixed effects, state fixed effects, and all controls. Standard errors clustered by state are shown in parentheses.

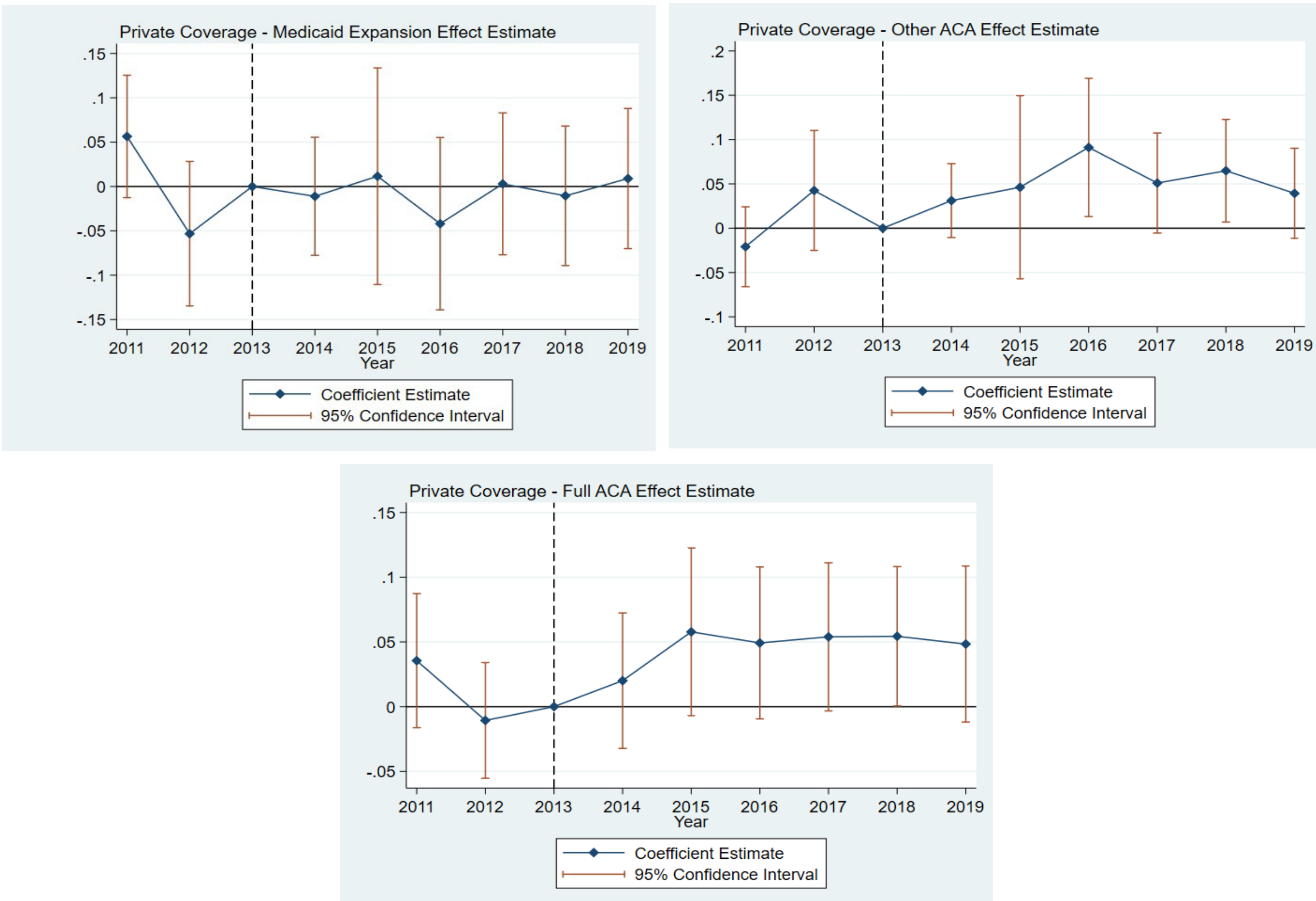
* p<0.1, ** p<0.05, *** p<0.01

Figure 4. Event Study - Any Coverage



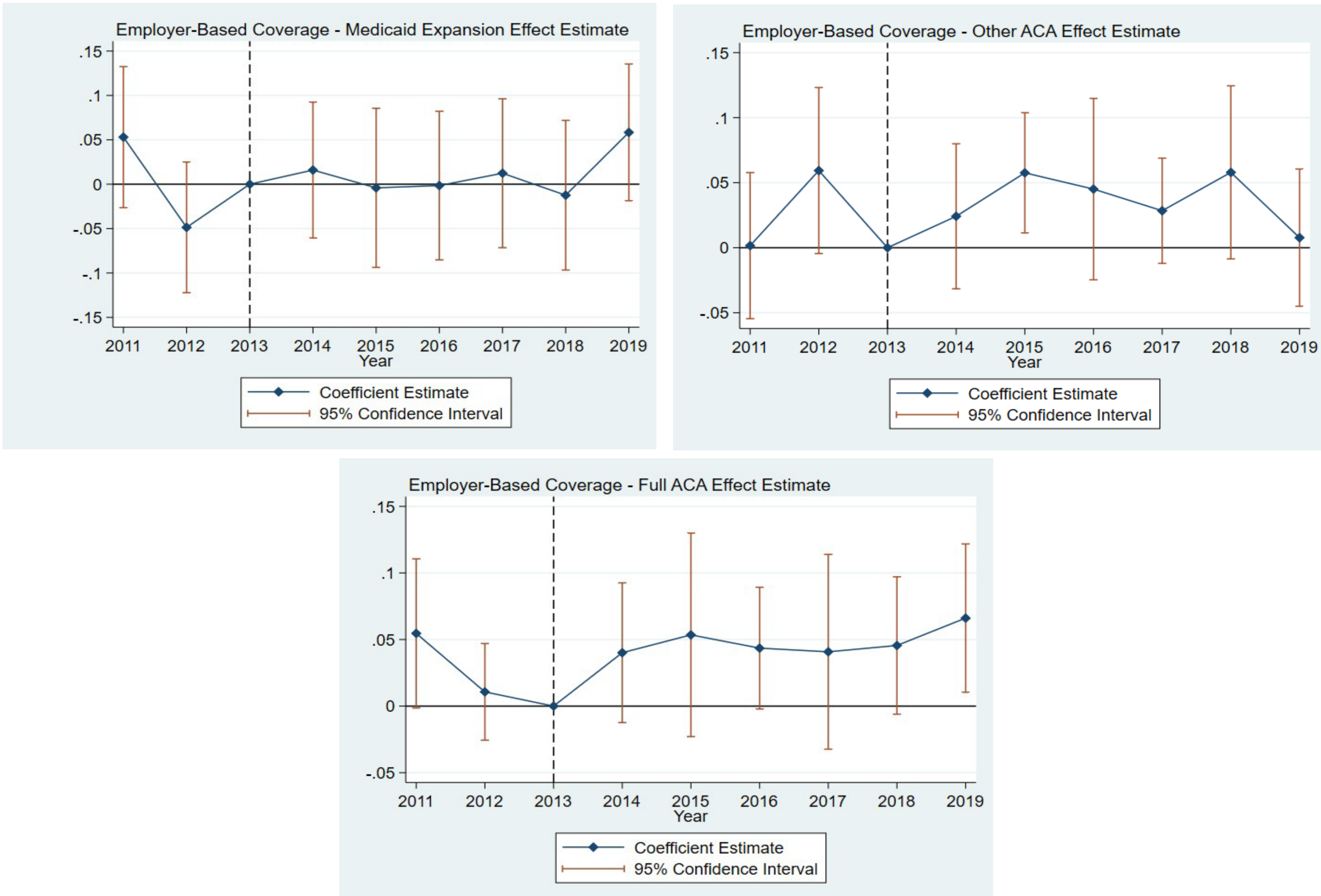
Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 5. Event Study - Private Coverage



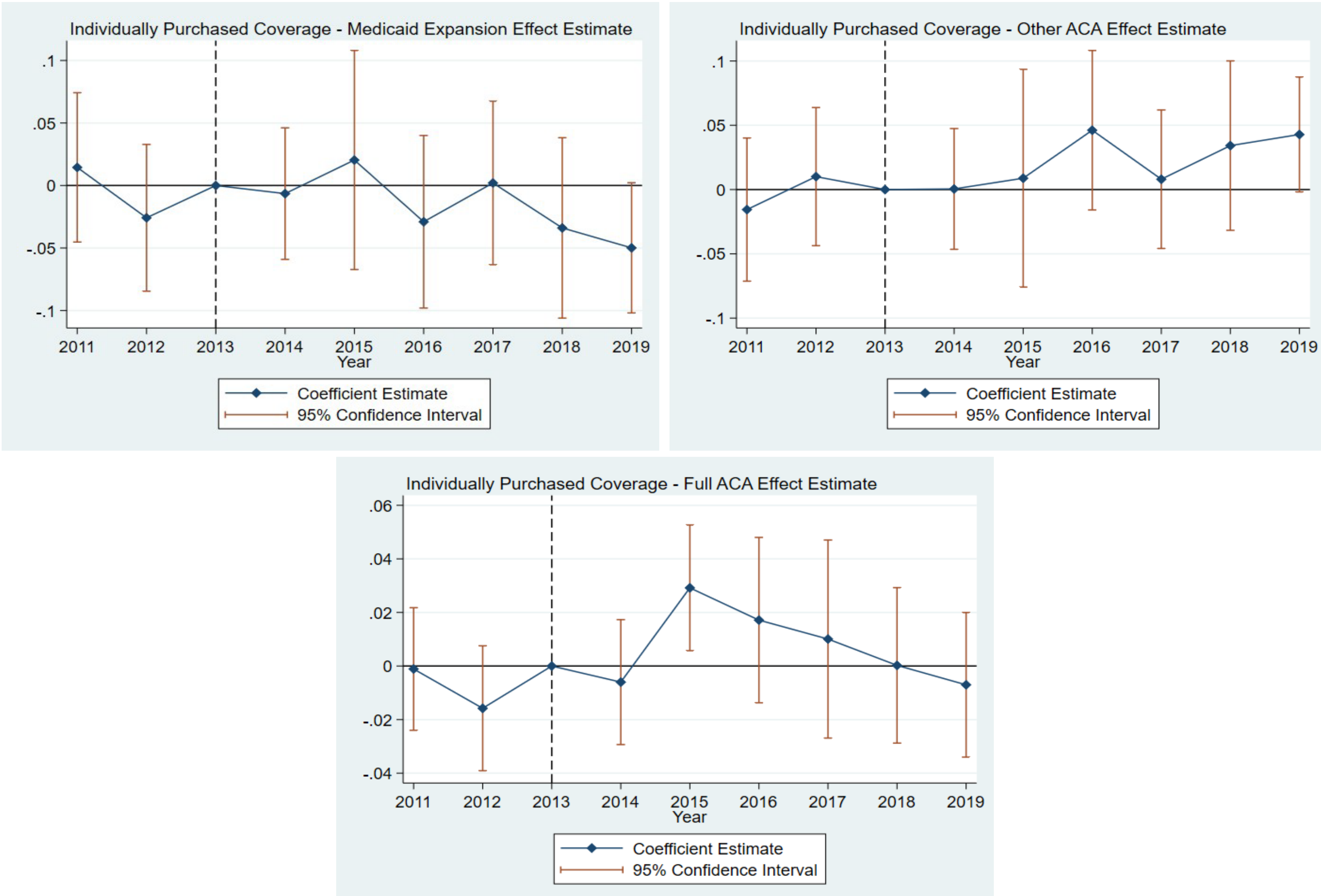
Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 6. Event Study - Employer/Union Coverage



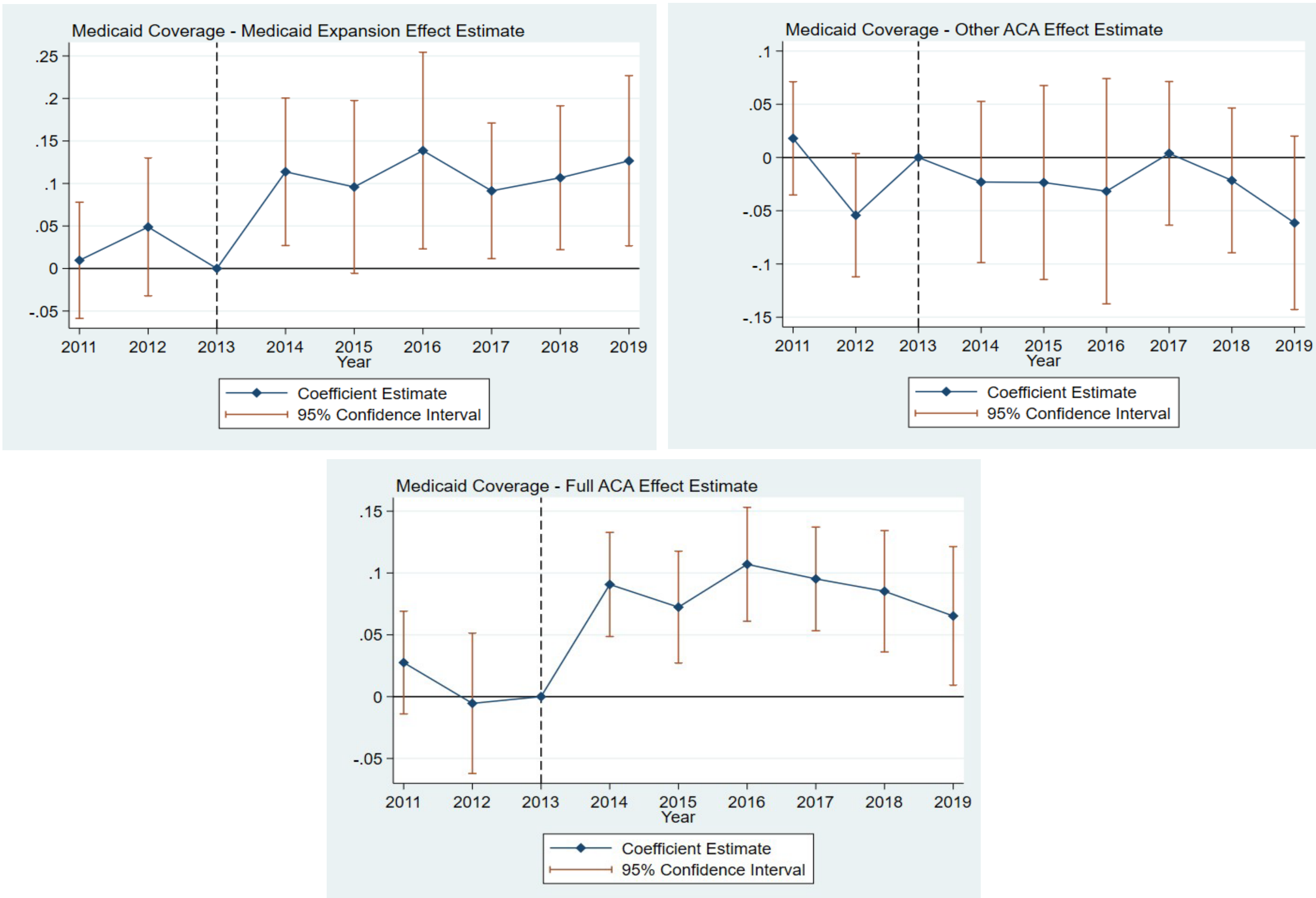
Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 7. Event Study - Individually Purchased Coverage



Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 8. Event Study - Medicaid Coverage



Notes: Data from the IPUMS-ACS for the years 2011-2019. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded.

Figure 5 shows event study plots when the outcome is private coverage. In the "Full ACA Effect" graph, the point estimates show a steady increase to 2015 but then level off at that point. For the "Other ACA Effect" graph, the point estimates increase up through 2016 before decreasing in 2017 and leveling off.

Figure 8 shows event study plots when the outcome is Medicaid coverage. In the "Full ACA Effect" graph, the point estimates show a similar trend to the point estimates in the any coverage "Full ACA Effect" graph, except for a slight dip in 2015 from 2014 and a larger decrease for the years 2017 through 2019.

1.6.2 Robustness Checks

I test the robustness of the results by varying the model and data specifications. Tables 4-8 show the results of the robustness checks. The tables show implied effects. Each table is for a separate type of coverage. In each table, column (1) shows the main estimates from Table 2. Columns (2)-(4) show estimates when varying the control variables used in the model. Columns (5)-(6) show estimates when varying the years used for the uninsured rate variable in the model. Column (7) shows estimates when dropping individuals ages 20-25 years old (who could have been affected by the dependent coverage mandate). Column (8) shows estimates when including individuals in states that expanded their Medicaid programs in 2015-2019. Column (9) shows estimates when including the year 2010 (which was the year the dependent coverage mandate went into effect). Column (10) shows estimates when including the year 2010 and dropping individuals ages 20-25 years old.

Starting with columns (2)-(4), the results suggest little impact from varying which control variables are used; this is the case for all outcomes. Some of the estimates have improved statistical significance when using all the controls, but the coefficient estimates do not change

Table 4. Robustness Checks (Implied Effects) - Any Coverage

	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add Family Controls (4)	Unins. Rate 2012 (5)	Unins. Rate 2013 (6)	Drop 20- to 25-year olds (7)	Include All States (8)	Include Year 2010 (9)	2010, Drop 20-25 (10)
Medicaid	**0.085*****	0.082***	0.086***	0.087***	0.068***	0.089***	0.081***	0.079***	0.074***	0.073***
expansion	**(0.017)**	(0.017)	(0.017)	(0.017)	(0.017)	(0.018)	(0.019)	(0.014)	(0.015)	(0.016)
ACA without	**0.035****	0.038**	0.035**	0.034**	0.037***	0.021	0.041**	0.041***	0.038***	0.042***
Medicaid exp.	**(0.015)**	(0.015)	(0.016)	(0.016)	(0.014)	(0.016)	(0.018)	(0.014)	(0.013)	(0.014)
Full ACA	**0.120*****	0.120***	0.120***	0.121***	0.106***	0.110***	0.122***	0.119***	0.112***	0.114***
with Medicaid exp.	**(0.006)**	(0.006)	(0.006)	(0.006)	(0.010)	(0.009)	(0.007)	(0.006)	(0.007)	(0.009)
Observations	**162,348**	162,348	162,348	162,348	162,348	162,348	152,486	184,935	180,194	169,335
Demographics	**Y**		Y	Y	Y	Y	Y	Y	Y	Y
Family controls	**Y**			Y	Y	Y	Y	Y	Y	Y
Economic controls	**Y**				Y	Y	Y	Y	Y	Y

Notes: Column (1) shows estimates from Table 2. Columns (2)-(3) show implied effects when varying the control variables used in the model. Columns (5)-(6) show implied effects when varying which years are used for the uninsured rates when estimating the model. Column (7) shows implied effects when dropping individuals ages 20-25 years old. Column (8) shows implied effects including states that expanded Medicaid in the years 2015-2019. Column (9) shows implied effects when including the year 2010. Column (10) shows implied effects when including the year 2010 and dropping individuals ages 20-25 years old. See Table 2 for notes on data used. Underlying models include year fixed effects and state effects. Standard errors clustered at the state-level are shown in parentheses.

* p<0.1, ** p<0.05, *** p<0.01

Table 5. Robustness Checks (Implied Effects) - Private Coverage

	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add Family Controls (4)	Unins. Rate 2012 (5)	Unins. Rate 2013 (6)	Drop 20- to 25- year olds (7)	Include All States (8)	Include Year 2010 (9)	2010, Drop 20-25 (10)
Medicaid	**-0.006**	-0.018	-0.012	-0.005	-0.010	0.001	-0.012	-0.001	-0.005	-0.005
expansion	**(0.025)**	(0.033)	(0.033)	(0.027)	(0.023)	(0.027)	(0.023)	(0.021)	(0.026)	(0.023)
ACA without	**0.046****	0.056*	0.052*	0.043*	0.040**	0.040*	0.055***	0.043**	0.043*	0.048**
Medicaid exp.	**(0.020)**	(0.030)	(0.028)	(0.022)	(0.018)	(0.024)	(0.018)	(0.017)	(0.023)	(0.020)
Full ACA	**0.040*****	0.038**	0.040**	0.038**	0.030*	0.041***	0.043***	0.043***	0.038***	0.042***
with Medicaid exp.	**(0.014)**	(0.015)	(0.016)	(0.017)	(0.015)	(0.012)	(0.013)	(0.014)	(0.013)	(0.012)
Observations	**162,348**	162,348	162,348	162,348	162,348	162,348	152,486	184,935	180,194	169,335
Demographics	**Y**		Y	Y	Y	Y	Y	Y	Y	Y
Family controls	**Y**			Y	Y	Y	Y	Y	Y	Y
Economic controls	**Y**				Y	Y	Y	Y	Y	Y

Notes: See notes for Table 4.

* p<0.1, ** p<0.05, *** p<0.01

Table 6. Robustness Checks (Implied Effects) - Employer-Union Coverage

	Main Esti-mates (1)	No Controls (2)	Add Demo. Controls (3)	Add Family Controls (4)	Unins. Rate 2012 (5)	Unins. Rate 2013 (6)	Drop 20- to 25-year olds (7)	Include All States (8)	Include Year 2010 (9)	2010, Drop 20-25 (10)
Medicaid	**0.011**	-0.002	0.001	0.008	0.006	0.016	0.011	0.010	0.016	0.019
expansion	**(0.025)**	(0.031)	(0.031)	(0.027)	(0.023)	(0.026)	(0.024)	(0.023)	(0.027)	(0.024)
ACA without	**0.016**	0.026	0.023	0.015	0.014	0.012	0.018	0.018	0.013	0.012
Medicaid exp.	**(0.020)**	(0.028)	(0.027)	(0.022)	(0.018)	(0.021)	(0.020)	(0.019)	(0.024)	(0.021)
Full ACA	**0.027***	0.024	0.025	0.023	0.020	0.028**	0.028**	0.027*	0.029**	0.031***
with Medicaid exp.	**(0.014)**	(0.015)	(0.016)	(0.016)	(0.014)	(0.013)	(0.013)	(0.014)	(0.012)	(0.011)
Observations	**162,348**	162,348	162,348	162,348	162,348	162,348	152,486	184,935	180,194	169,335
Demographics	**Y**		Y	Y	Y	Y	Y	Y	Y	Y
Family controls	**Y**			Y	Y	Y	Y	Y	Y	Y
Economic controls	**Y**				Y	Y	Y	Y	Y	Y

Notes: See notes for Table 4.

* p<0.1, ** p<0.05, *** p<0.01

Table 7. Robustness Checks (Implied Effects) - Individually Purchased Coverage

	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add Family Controls (4)	Unins. Rate 2012 (5)	Unins. Rate 2013 (6)	Drop 20- to 25-year olds (7)	Include All States (8)	Include Year 2010 (9)	2010, Drop 20-25 (10)
Medicaid	**-0.011**	-0.009	-0.008	-0.007	-0.009	-0.011	-0.016	-0.002	-0.019	-0.023*
expansion	**(0.016)**	(0.017)	(0.016)	(0.016)	(0.015)	(0.018)	(0.015)	(0.014)	(0.014)	(0.013)
ACA without	**0.025***	0.024	0.023	0.022	0.022	0.021	0.031**	0.019	0.027**	0.032***
Medicaid exp.	**(0.014)**	(0.015)	(0.014)	(0.014)	(0.014)	(0.015)	(0.013)	(0.012)	(0.011)	(0.010)
Full ACA	**0.013***	0.015*	0.015*	0.015*	0.013*	0.011	0.015*	0.017**	0.009	0.010
with Medicaid exp.	**(0.008)**	(0.008)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)	(0.007)	(0.008)	(0.008)
Observations	**162,348**	162,348	162,348	162,348	162,348	162,348	152,486	184,935	180,194	169,335
Demographics	**Y**		Y	Y	Y	Y	Y	Y	Y	Y
Family controls	**Y**			Y	Y	Y	Y	Y	Y	Y
Economic controls	**Y**				Y	Y	Y	Y	Y	Y

Notes: See notes for Table 4.

* p<0.1, ** p<0.05, *** p<0.01

Table 8. Robustness Checks (Implied Effects) - Medicaid Coverage

	Main Esti-mates (1)	No Controls (2)	Add Demo. Controls (3)	Add Family Controls (4)	Unins. Rate 2012 (5)	Unins. Rate 2013 (6)	Drop 20- to 25-year olds (7)	Include All States (8)	Include Year 2010 (9)	2010, Drop 20-25 (10)
Medicaid	**0.091*** **	0.100**	0.098**	0.092***	0.076**	0.091***	0.088***	0.073**	0.082***	0.079***
expansion	**(0.031)**	(0.040)	(0.039)	(0.033)	(0.029)	(0.028)	(0.031)	(0.030)	(0.030)	(0.029)
ACA without	**-0.012**	-0.021	-0.019	-0.011	-0.001	-0.024	-0.009	0.004	-0.005	-0.003
Medicaid exp.	**(0.027)**	(0.036)	(0.035)	(0.029)	(0.027)	(0.021)	(0.027)	(0.027)	(0.026)	(0.025)
Full ACA	**0.079*** **	0.079***	0.079***	0.081***	0.075***	0.067***	0.079***	0.077***	0.077***	0.076***
with Medicaid exp.	**(0.014)**	(0.016)	(0.017)	(0.017)	(0.010)	(0.017)	(0.014)	(0.013)	(0.013)	(0.014)
Observations	**162,348**	162,348	162,348	162,348	162,348	162,348	152,486	184,935	180,194	169,335
Demographics	**Y**		Y	Y	Y	Y	Y	Y	Y	Y
Family controls	**Y**			Y	Y	Y	Y	Y	Y	Y
Economic controls	**Y**				Y	Y	Y	Y	Y	Y

Notes: See notes for Table 4.

* p<0.1, ** p<0.05, *** p<0.01

much. This gives me confidence that there were not significant changes between expansion and non-expansion states and between low and high uninsured rate states that might confound analysis.

Turning to columns (5)-(6), I focus on the any coverage table. The full ACA effect estimates for any coverage are slightly attenuated. For column (5), this is driven by attenuation of the Medicaid expansion estimate, whereas for column (6), this is driven by attenuation of the other ACA components estimate. Overall, the estimates for all outcomes are robust to the alternative uninsurance rate years. Given the larger sample size when using both the years 2012-2013 for the uninsured rate variable, I think it is more appropriate to use both years.

For column (7), the estimates are largely consistent for all outcomes. Across all outcomes, the estimates suggest a similar full ACA effect. Regarding the ACA without Medicaid expansion effect, column (7) has slightly larger estimates. The estimates, though, are not different enough to suggest a different interpretation of the results. I still think it is appropriate to include this group in the main estimates as some of them would have been affected by the policy.

For column (8), the estimates are largely consistent for all outcomes. Including these states does not affect the results much, so I still think it is appropriate to exclude these states from the main estimates. This allows me to avoid issues associated with the two-way fixed effects estimator when a policy has staggered adoption.

For columns (9) and (10), the estimates are largely consistent for all outcomes. I still think it is appropriate to exclude the year 2010 to avoid both the implementation of the dependent care mandate and to also avoid any lingering effects from the Great Recession. Although individuals ages 20-25 could have benefited from the dependent care mandate, they could have also benefited from other aspects of the ACA, so I think it is best to keep them in the sample.

1.6.3 Heterogeneity Results

I also study the heterogeneous effects of the ACA on SSDI beneficiaries without Medicare coverage. Tables 9-14 show the corresponding implied effects. Each table shows estimates for a particular control variable. For each examined control variable, I split the sample into two subsamples.[22]

Table 9 shows the heterogeneous effects by education. The sample is split into individuals with "high school education or less" and individuals with "some college or higher." Column (1) suggests that for individuals with high school education or less the ACA increased health insurance coverage in Medicaid expansion states by 11.9 percentage points and increased coverage in non-expansion states by 5.6 percentage points; for individuals with some college or higher, the ACA increased health insurance coverage in Medicaid expansion states by 12.8 percentage points and increased coverage in non-expansion states by 3.5 percentage points. Each of the estimates is statistically significant at the 1 percent level, except the "ACA without Medicaid exp." estimate for individuals with some college or higher.

Table 10 shows heterogeneous effects by age. The sample is split between individuals ages 20-49 and individuals ages 50-59. Column (1) suggests that for individuals ages 20-49 the ACA increased health insurance coverage by 13.2 percentage points in Medicaid expansion states and by 3.7 percentage points in non-expansion states. For individuals ages 50-59, the ACA increased coverage by 11.6 percentage points in Medicaid expansion states and by 5.2 percentage points in non-expansion states. The Full ACA estimates are statistically significant at

[22] I do this to keep the subsamples a modest size. I attempt to create subsamples of equal size or along a particular margin of interest.

Table 9. Heterogeneity Results (Implied Effects) - Education

	Any Covg	Private Coverage			Public Covg
Dependent Variable:	Any coverage (1)	Any private (2)	Employer-union coverage (3)	Indiv. purch. coverage (4)	Medicaid (5)
High school education or less (2012/2013 uninsured rate=0.186, N=96,715)					
Medicaid	0.063***	0.015	0.030	-0.008	0.050
expansion	(0.018)	(0.035)	(0.027)	(0.019)	(0.044)
ACA without	0.056***	0.025	0.006	0.020	0.017
Medicaid exp.	(0.014)	(0.027)	(0.018)	(0.017)	(0.036)
Full ACA	0.119***	0.040*	0.036*	0.012	0.067***
with Medicaid exp.	(0.010)	(0.021)	(0.018)	(0.010)	(0.023)
Some college or higher (2012/2013 uninsured rate=0.155, N=65,633)					
Medicaid	0.093***	-0.025	-0.027	0.021	0.111***
expansion	(0.028)	(0.022)	(0.029)	(0.029)	(0.023)
ACA without	0.035	0.066***	0.039	0.005	-0.012
Medicaid exp.	(0.026)	(0.018)	(0.025)	(0.025)	(0.018)
Full ACA	0.128***	0.041***	0.012	0.026*	0.099***
with Medicaid exp.	(0.009)	(0.012)	(0.013)	(0.014)	(0.014)

Notes: See Table 2 for notes about data, model, and estimation. Sample is stratified based on criteria shown in above table.

* p<0.1, ** p<0.05, *** p<0.01

Table 10. Heterogeneity Results (Implied Effects) - Age

	Any Covg	**Private Coverage**			**Public Covg**
Dependent Variable:	Any coverage (1)	Any private (2)	Employer-union coverage (3)	Indiv. purch. coverage (4)	Medicaid (5)
Age 20-49 (2012/2013 uninsured rate=0.181, N=82,778)					
Medicaid	0.095***	-0.002	0.022	-0.019	0.109***
expansion	(0.017)	(0.029)	(0.028)	(0.020)	(0.032)
ACA without	0.037**	0.030	0.005	0.025*	-0.007
Medicaid exp.	(0.014)	(0.023)	(0.021)	(0.013)	(0.023)
Full ACA	0.132***	0.027	0.027	0.006	0.102***
with Medicaid exp.	(0.010)	(0.018)	(0.018)	(0.014)	(0.020)
Age 50-59 (2012/2013 uninsured rate=0.165, N=79,570)					
Medicaid	0.064**	-0.020	-0.029	0.022	0.060*
expansion	(0.025)	(0.037)	(0.031)	(0.027)	(0.035)
ACA without	0.052**	0.071**	0.062**	-0.006	-0.003
Medicaid exp.	(0.024)	(0.031)	(0.027)	(0.024)	(0.028)
Full ACA	0.116***	0.051**	0.033**	0.016	0.057***
with Medicaid exp.	(0.009)	(0.020)	(0.016)	(0.012)	(0.020)

Notes: See Table 2 for notes about data, model, and estimation. Sample is stratified based on criteria shown in above table.

* p<0.1, ** p<0.05, *** p<0.01

Table 11. Heterogeneity Results (Implied Effects) - Race/Ethnicity

	Any Covg	**Private Coverage**			**Public Covg**
Dependent Variable:	Any coverage (1)	Any private (2)	Employer-union coverage (3)	Indiv. purch. coverage (4)	Medicaid (5)
Non-Hispanic White (2012/2013 uninsured rate=0.160, N=100,553)					
Medicaid	0.066***	0.050	0.057*	-0.005	0.029
expansion	(0.020)	(0.035)	(0.031)	(0.024)	(0.043)
ACA without	0.036*	0.004	-0.022	0.026	0.025
Medicaid exp.	(0.019)	(0.029)	(0.028)	(0.019)	(0.037)
Full ACA	0.101***	0.055***	0.034**	0.021	0.054**
with Medicaid exp.	(0.006)	(0.020)	(0.014)	(0.013)	(0.023)
All other (2012/2013 uninsured rate=0.192, N=61,795)					
Medicaid	0.099***	-0.060**	-0.043	-0.010	0.147***
expansion	(0.027)	(0.026)	(0.032)	(0.019)	(0.037)
ACA without	0.058**	0.078***	0.051**	0.023*	-0.021
Medicaid exp.	(0.024)	(0.020)	(0.024)	(0.012)	(0.032)
Full ACA	0.156***	0.018	0.008	0.013	0.125***
with Medicaid exp.	(0.012)	(0.015)	(0.020)	(0.013)	(0.018)

Notes: See Table 2 for notes about data, model, and estimation. Sample is stratified based on criteria shown in above table.

* p<0.1, ** p<0.05, *** p<0.01

Table 12. Heterogeneity Results (Implied Effects) - Marital Status

	Any Covg	**Private Coverage**			**Public Covg**
Dependent Variable:	Any coverage	Any private	Employer-union coverage	Indiv. purch. directly	Medicaid
	(1)	(2)	(3)	(4)	(5)
Married (2012/2013 uninsured rate=0.152, N=60,453)					
Medicaid	0.044***	0.005	0.015	-0.015	0.054**
expansion	(0.014)	(0.030)	(0.037)	(0.020)	(0.026)
ACA without	0.056***	0.048**	0.025	0.031**	-0.001
Medicaid exp.	(0.012)	(0.023)	(0.033)	(0.015)	(0.018)
Full ACA	0.100***	0.052**	0.040**	0.016	0.052***
with Medicaid exp.	(0.008)	(0.020)	(0.016)	(0.013)	(0.019)
Not married (2012/2013 uninsured rate=0.185, N=101,895)					
Medicaid	0.085***	0.012	0.027	-0.003	0.087**
expansion	(0.028)	(0.035)	(0.032)	(0.012)	(0.038)
ACA without	0.047*	0.034	0.003	0.024**	0.003
Medicaid exp.	(0.027)	(0.032)	(0.028)	(0.010)	(0.035)
Full ACA	0.132***	0.046***	0.030**	0.020***	0.091***
with Medicaid exp.	(0.007)	(0.013)	(0.014)	(0.006)	(0.014)

Notes: See Table 2 for notes about data, model, and estimation. Sample is stratified based on criteria shown in above table.

* p<0.1, ** p<0.05, *** p<0.01

Table 13. Heterogeneity Results (Implied Effects) - Individual's Sex

	Any Covg	**Private Coverage**			**Public Covg**
Dependent Variable:	Any coverage (1)	Any private (2)	Employer-union coverage (3)	Indiv. purch. directly (4)	Medicaid (5)
Female (2012/2013 uninsured rate=0.173, N=84,838)					
Medicaid	0.090***	-0.027	-0.031	-0.010	0.109***
expansion	(0.026)	(0.020)	(0.022)	(0.015)	(0.032)
ACA without	0.039*	0.040***	0.038**	0.011	-0.006
Medicaid exp.	(0.023)	(0.014)	(0.015)	(0.011)	(0.024)
Full ACA	0.129***	0.013	0.007	0.002	0.102***
with Medicaid exp.	(0.010)	(0.014)	(0.016)	(0.010)	(0.019)
Male (2012/2013 uninsured rate=0.174, N=77,510)					
Medicaid	0.060***	-0.005	0.048	-0.012	0.068
expansion	(0.022)	(0.041)	(0.031)	(0.028)	(0.049)
ACA without	0.052**	0.071*	0.004	0.031	-0.017
Medicaid exp.	(0.020)	(0.037)	(0.026)	(0.027)	(0.046)
Full ACA	0.112***	0.066***	0.052***	0.019***	0.051***
with Medicaid exp.	(0.010)	(0.017)	(0.017)	(0.006)	(0.016)

Notes: See Table 2 for notes about data, model, and estimation. Sample is stratified based on criteria shown in above table.

* p<0.1, ** p<0.05, *** p<0.01

Table 14. Heterogeneity Results (Implied Effects) - Number of Children

	Any Covg	**Private Coverage**			**Public Covg**
Dependent Variable:	Any coverage (1)	Any private (2)	Employer-union coverage (3)	Indiv. purch. directly (4)	Medicaid (5)
Zero children (2012/2013 uninsured rate=0.163, N=102,256)					
Medicaid	0.037*	-0.002	0.003	0.015	0.055
expansion	(0.022)	(0.043)	(0.034)	(0.030)	(0.047)
ACA without	0.059***	0.062	0.025	0.019	-0.011
Medicaid exp.	(0.021)	(0.037)	(0.031)	(0.028)	(0.043)
Full ACA	0.096***	0.060***	0.029*	0.034***	0.044**
with Medicaid exp.	(0.006)	(0.021)	(0.015)	(0.012)	(0.019)
1+ children (2012/2013 uninsured rate=0.190, N=60,092)					
Medicaid	0.131***	0.000	0.023	-0.018	0.126***
expansion	(0.024)	(0.019)	(0.024)	(0.020)	(0.031)
ACA without	0.022	0.021	0.004	0.018	0.000
Medicaid exp.	(0.020)	(0.016)	(0.017)	(0.012)	(0.022)
Full ACA	0.153***	0.021*	0.027*	-0.000	0.126***
with Medicaid exp.	(0.013)	(0.011)	(0.016)	(0.015)	(0.020)

Notes: See Table 2 for notes about data, model, and estimation. Sample is stratified based on criteria shown in above table.

* p<0.1, ** p<0.05, *** p<0.01

the 1 percent level, and the "ACA without Medicaid exp." estimates are statistically significant at the 5 percent level. For individuals in expansion states, the larger increase in coverage for individuals ages 20-49 (13.2 percentage points versus 11.6 percentage points) was driven by larger increases in Medicaid coverage (10.2 percentage points versus 5.7 percentage points).

Table 11 shows heterogeneous effects by race/ethnicity. The sample is split by non-Hispanic White individuals and all other individuals. Column (1) suggests that for non-Hispanic White individuals the ACA increased health insurance coverage by 10.1 percentage points in Medicaid expansions states and by 3.6 percentage points in non-expansion states. For all other individuals, the ACA increased health insurance coverage by 15.6 percentage points in Medicaid expansion states and by 5.8 percentage points in non-expansion states. The Full ACA estimates are statistically significant at the 1 percent level, and the "ACA without Medicaid exp." estimates are statistically significant at the 10 and 5 percent levels for non-Hispanic White and all other individuals, respectively. The estimates suggest larger gains for all other individuals in both expansion and non-expansion states. In non-expansion states, this was driven by larger gains in any private coverage. In expansion states, this was driven by larger gains in Medicaid coverage.

Table 12 shows heterogeneous effects by marital status. The sample is split between married individuals and unmarried individuals. For married individuals, column (1) suggests the ACA increased health insurance coverage by 10.0 percentage points in Medicaid expansion states and by 5.6 percentage points in non-expansion states. For unmarried individuals, health insurance coverage increased by 13.2 percentage points in Medicaid expansion states and by 4.7 percentage points in non-expansion states. All estimates are statistically significant at the 1 percent level, except the "ACA without Medicaid exp." estimate for unmarried individuals, which is statistically significant at the 10 percent level. For expansion states, column (5) suggests that the larger increase for unmarried individuals was driven by a larger increase in Medicaid coverage.

Table 13 shows heterogeneous effects by individual's sex. For females, column (1) suggests the ACA increased health insurance by 12.9 percentage points in Medicaid expansion states and by 3.9 percentage points in non-expansion states. For males, the ACA increased health insurance coverage by 11.2 percentage points in Medicaid expansion states and by 5.2 percentage points in non-expansion states. The Full ACA estimates are statistically significant at the 1 percent level, and the "ACA without Medicaid exp." estimates are statistically significant at the 10 and 5 percent levels for females and males, respectively. For expansion states, column (5) suggests the larger increase for females was driven by a larger increase in Medicaid coverage.

Table 14 shows heterogeneous effects by number of children. The sample is split between individuals with zero children and individuals with one or more children. For individuals with zero children, column (1) suggests the ACA increased health insurance coverage by 9.6 percentage points in Medicaid expansion states and by 5.9 percentage points in non-expansion states. For individuals with one or more children, the ACA increased health insurance coverage by 15.3 percentage points in Medicaid expansion states and by 2.2 percentage points in non-expansion states. All estimates are statistically significant at the 1 percent level, except the "ACA without Medicaid exp." estimate for individuals with one or more children, which is not statistically significant. For expansion states, the larger increase for individuals with one or more children appears driven by a larger increase in Medicaid coverage (from column (5)).

1.7 Discussion

In this study, I present new evidence about the effects of the ACA on the health insurance coverage of SSDI beneficiaries in the Medicare waiting period. In Medicaid expansion states, I estimate a 12.0 percentage point increase in health insurance coverage, and in non-expansion states, I estimate a 3.5 percentage point increase in coverage. Using these estimates and a weighted average of Medicaid expansion state and non-expansion state populations, I estimate that the ACA increased health insurance coverage by 8.3 percentage points. Regarding private coverage, states that expanded Medicaid experienced a larger increase in employer-based coverage (increase of 2.7 percentage points), whereas non-expanding states saw a larger increase in individually purchased coverage (2.5 percentage points).

The results suggest substantial health insurance coverage gains from the ACA for the non-Medicare-eligible SSDI group. The Medicaid expansions were the main driver of coverage gains in expansion states, though the private market reforms also had an effect. This suggests that if additional states expand their Medicaid programs, then SSDI beneficiaries in those states could see further gains in health insurance coverage. State policymakers in non-expansion states should consider the gains that have occurred in expansion states. Additionally, federal policymakers should consider whether the ACA ushered in significant enough changes to mute the effect of ending the SSDI Medicare waiting period.

Relative to the overall population, SSDI beneficiaries in the Medicare waiting period saw larger coverage gains from the ACA. The closest paper to my study is Courtemanche, Fazlul, et al. (2019). The study investigates the effects of the ACA on the overall working-age population with a four-year post period. The study estimates that, in Medicaid expansion states, health insurance coverage increased by 8.7 percentage points (relative to my estimate of 12.0

percentage points for the non-Medicare-eligible SSDI population). The study estimates that, in non-expansion states, coverage increased by 3.6 percentage points (relative to my estimate of 3.5 percentage points for the non-Medicare-eligible SSDI population). Our studies produce similar estimates for the effects in non-expansion states, but my study produces a larger number for the effects in Medicaid expansion states. This suggests greater health insurance coverage gains for the SSDI waiting period population relative to the overall working-age population.

Based on the heterogeneity results, individuals in Medicaid expansion states always experienced larger gains in health insurance coverage than individuals in non-expansion states, regardless of examined subgroup. In Medicaid expansion states, some of the largest gains were by individuals who were not non-Hispanic White and by individuals with one or more children. It might seem that individuals with zero children should have seen larger gains from Medicaid expansions (because the Medicaid expansions targeted childless adults), but the estimates suggest otherwise. Another set of subgroups with noteworthy results are those based on marital status. In Medicaid expansion states, unmarried individuals saw much larger gains than married individuals.

This study is not without limitations. First, regarding the ACS survey questions about income sources, the survey also asks about "Supplemental Security Income (SSI)." Individuals might mix up the Social Security program and the SSI program and misreport their income for these programs. If this occurred, I could inadvertently include non-SSDI individuals in the sample (if they reported SSI income as Social Security income) or inadvertently exclude SSDI individuals from the sample (if they reported Social Security income as SSI income). I cannot directly test this misreporting, so it remains a limitation of the study.

Another limitation is misreporting of Medicare coverage. Because individuals must report each of their health insurance coverage types, they might mistake Medicare coverage as another type of coverage (such as Medicaid) or vice-versa. If an SSDI individual has Medicare coverage but does not report it, I inadvertently include them in the sample. If an SSDI individual does not have Medicare coverage but reports having it, I inadvertently exclude them from the sample. This misreporting could also influence my main outcomes variables (because my main outcomes are health insurance coverage types). I cannot directly test this misreporting, so it remains a limitation of the study.

If applications to the SSDI program changed as a result of the ACA, then this could lead to biased estimates. Prospective SSDI applicants might perceive the SSDI waiting period as less burdensome due to the increased health insurance options from the ACA. If more people decided to apply to the program as a result (and were subsequently approved), then the new marginal SSDI enrollees could have looked different than the existing SSDI population prior to the ACA. This might affect how we interpret the results from the study. Regarding the ACA Medicaid expansions, the evidence is mixed whether SSDI applications changed as a result of the ACA (Anand et al., 2018; Schmidt et al., 2020; Staiger et al., 2023). I find no literature discussing whether or not the ACA private market changes had an effect on SSDI application decisions.

To continue this line of research, work could be done to investigate how the large gains in health insurance coverage from the ACA translated to changes in health care utilization and expenditure. This data is available in the Medical Expenditure Panel Survey (MEPS), but the restricted MEPS would be required for the identification strategy as it includes state-level identifiers. Analyzing outcomes from the MEPS could improve our understanding of the welfare gains from the ACA for SSDI beneficiaries waiting for Medicare coverage.

CHAPTER 2: What Effect Did Medicare Part D Have on SSDI Medicare Beneficiaries? A Look at Prescription Drug Coverage, Utilization, and Expenditures

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2.1 Introduction

The Medicare Modernization Act of 2003 ushered in the most significant change to Medicare since the program's creation in 1965. Most significantly, it introduced Medicare Part D in 2006, which expanded prescription drug coverage to all Medicare beneficiaries. Before Medicare Part D, some Medicare beneficiaries obtained prescription drug coverage from other sources, including employer-provided health insurance, Medigap plans, Medicare Advantage (MA) plans, and Medicaid.[23] However, over 30 percent of the 44 million Medicare beneficiaries lacked prescription coverage (Duggan et al., 2008).

To understand the impact of the Medicare Part D program, I analyze its effects on prescription drug coverage, annual prescription drug utilization, and annual prescription drug expenditures. I look at these outcomes for the Part D eligible SSDI population.[24] Nearly all literature regarding Medicare Part D has focused on the elderly population, so this paper contributes to the literature by analyzing the policy's effect on the SSDI population.

Analysis for the SSDI population is important because the effects of Medicare Part D may have been different for this population. Before Part D, people with disabilities likely had more difficulties accessing prescription drug insurance from private insurers compared to the

[23] Plans under Medicare Part C were called "Medicare+Choice" plans up until 2003 and "Medicare Advantage" plans starting in 2003; I refer to these plans as Medicare Advantage plans throughout the paper, regardless of time period.

[24] The breakdown of Medicare beneficiaries is as follows: the elderly population made up 84 percent, the SSDI population made up 15.5 percent, and the ESRD population made up 0.5 percent, as of 2006 (Social Security Administration, 2008). Some individuals qualify for SSDI payments because of ESRD; I count these individuals in the ESRD population in the statistics above because they qualify for Medicare benefits much sooner than other SSDI beneficiaries.

elderly. In many state individual health insurance markets, insurers could limit coverage based on pre-existing health conditions (Claxton et al., 2016), which meant it likely was not an option for many people with disabilities. Although Medigap and MA plans could have been options for some SSDI Medicare beneficiaries, this was not always the case. For Medigap, federal regulations govern policies for the age 65 and older population, whereas regulation is left to the states for the under age 65 population. For those under age 65, these differences in state regulations result in some states having substantially less Medigap plan options and more barriers to getting coverage (Armour & O'Hanlon, 2019). Regarding MA plans, they are usually managed care plans which restrict access to certain providers. This may dissuade people with disabilities to participate because many have a lot of health care needs. Because of these barriers, the inception of Part D should have resulted in larger coverage gains and less substitution away from private coverage for the Part D eligible SSDI population. Ultimately, the results of my study bear this out.

Using difference-in-differences estimation and data from the Medical Expenditure Panel Survey (MEPS), I compare prescription drug coverage, annual prescription drug utilization, and annual prescription drug expenditures between SSDI individuals with and without Medicare Part D eligibility, before and after the policy change. Regarding Medicare eligibility, new SSDI beneficiaries become eligible for Medicare after an initial 24-month waiting period. I define the treatment group to be SSDI beneficiaries who have completed the 24-month waiting period and the control group to be SSDI beneficiaries still in the 24-month waiting period. Given that both the treatment and control groups are composed of individuals who are SSDI beneficiaries, I assume they have similar demand for prescription drug insurance coverage. For the Part D eligible SSDI population, I estimate that the policy increased prescription drug coverage by 18 percentage points and decreased annual out-of-pocket prescription drug expenditure by $526 (a decrease of 42 percent from the pre-reform mean). Additionally, the estimates suggest modest substitution away from private prescription drug coverage (decrease of 5.7 percentage points) and little decrease in annual private insurance prescription drug expenditure ($31). This would suggest large welfare gains from the policy for the Part D eligible SSDI population.

The rest of the paper is organized as follows. In Section 2.2, I discuss relevant literature. In Section 2.3, I discuss the data used for the study. In Section 2.4, I discuss the methodology used for the study. In Section 2.5, I present the results from the empirical model. In Section 2.6, I discuss the results from the empirical model and conclude the paper.

2.2 Literature Review

Literature regarding Medicare Part D has primarily focused on the elderly population. These studies find that the policy increased prescription drug insurance coverage (Asfaw, 2019; Engelhardt & Gruber, 2011; Levy & Weir, 2010), increased prescription drug utilization (Asfaw, 2019; Duggan & Morton, 2010; Ketcham & Simon, 2008; Khan & Kaestner, 2009; Lichtenberg & Sun, 2007; Yin et al., 2008), and increased prescription drug expenditure (Engelhardt & Gruber, 2011; Lichtenberg & Sun, 2007).

Among these studies, Engelhardt and Gruber (2011) is the most relevant to my study. For evaluating changes in prescription drug coverage, utilization, and expenditures, the authors use difference-in-differences estimation and MEPS data to compare outcomes between elderly individuals with and without Medicare eligibility, before and after the policy change. I follow the same approach but with different treatment and control groups. I compare outcomes between SSDI beneficiaries with and without Medicare eligibility, before and after the policy change. Another point of differentiation is that when estimating the effects on utilization and expenditures, Engelhardt and Gruber (2011) estimate a local average treatment effect, which is the effect for individuals induced into treatment because of the policy. I estimate an intent-to-treat effect, which measures the effect of the policy across the entire sample.

Prior literature regarding Medicare Part D and the SSDI population is scant.[25] I am aware of only two papers that discuss Medicare Part D's effect for my outcomes of interest. Nelson et al. (2014) evaluate the effect of Medicare Part D on the combined group of SSDI and ESRD Medicare beneficiaries.[26] Their estimates suggest little change in both the number of prescription drugs filled and total drug expenditure, though the estimates are fairly imprecise. For categories of drug expenditure, they estimate significant decreases in out-of-pocket expenditure (55 percent) and private insurance expenditure (63 percent).

Chandra et al. (2017) also analyze the impact of Medicare Part D on the combined group of SSDI and ESRD Medicare beneficiaries. The authors evaluate the impact of Medicare Part D on beneficiary prescription drug expenditure, prescription drug utilization, and hospitalizations. Their estimates suggest a large increase in annual total drug expenditure ($944), little change in annual prescription drug utilization (decrease of 0.4 fills), and a decrease in the probability of hospitalization (5.3 percentage points). The authors also develop subsample estimates split by Medicaid coverage status. For each outcome, the subsample estimates are relatively similar to the corresponding overall estimates.

Neither study evaluates changes in prescription drug insurance coverage nor public drug expenditure. The goals of this paper are to estimate Medicare Part D's impact on these previously

[25] Park and Martin (2017) survey the literature between the years 2010 and 2015 for Medicare Part D's impact on prescription drug utilization and prescription drug out-of-pocket expenditure, and they list only one paper (Nelson et al., 2014) that discusses the SSDI population.
[26] Although my analysis focuses only on SSDI Medicare beneficiaries, my estimates are robust to including ESRD Medicare beneficiaries (see robustness checks in Subsection 2.5.4).

unstudied outcomes of interest and use a new identification strategy to estimate the impact on some of the already studied outcomes.

2.3 Data

This paper uses data from the public-use version of the MEPS. The MEPS is a nationally representative survey of the U.S. civilian noninstitutionalized population conducted by the Agency for Healthcare Research and Quality. Drawn from respondents to the prior year's National Health Interview Survey, the MEPS collects data from households using a two-year overlapping panel design with a focus on medical care consumption. A new panel of sample households is selected each year, where households in each panel undergo five rounds of interviews over a two-and-a-half-year period. For this study, my analysis focuses on survey answers from the end of each calendar year from 2002 to 2009. I do not include additional post-reform years to avoid any confounding effects from the Patient Protection and Affordable Care Act (ACA). The ACA reduced the well-known Medicare Part D "coverage gap," where plan members originally had 100 percent coinsurance after an initial coverage limit.[27] It phased down coinsurance in the coverage gap from 100 percent to 25 percent between 2011 and 2020 (KFF, 2010). Additionally, in 2010, individuals who reached the coverage gap could receive a $250 rebate. For individuals with Part D plans, this reduction in cost-sharing could affect their prescription drug utilization and expenditures, which would confound analysis related to these outcomes.

For this study, the primary pieces of the MEPS I use are the household component consolidated data files and the prescribed medicines files.[28] The former contain most of the data used in the analysis, including data for prescription drug insurance type, prescription drug

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[27] For more information about Medicare Part D cost-sharing before the ACA, see Hoadley et al. (2008).
[28] I also use the medical conditions files, which include respondents' medical diagnoses.

utilization, prescription drug expenditures, demographics, and census region of residence. The MEPS delineates prescription drug coverage and prescription drug expenditures by various types of payment sources, including: private group and non-group insurance, Medicare, Medicaid, out-of-pocket, and other classifications. However, the MEPS does not reconcile reported differences in drug coverage and drug expenditures (Agency for Healthcare Research and Quality, 2008); someone can be reported as having expenditure for an insurance coverage type but themselves report not having that same insurance coverage type. To account for this, I measure someone as having a coverage type if they report having that coverage type or if they are reported as having prescription drug expenditure for that coverage type, as is common in the literature.

The MEPS also includes a field for Social Security income. Individuals who have paid enough years of Social Security taxes can claim Social Security retirement benefits as early as age 62. The only individuals who can qualify for Social Security income under age 62 are those receiving SSDI benefits, survivor benefits, or both. Widows and widowers can receive survivor benefits as early as age 60 if they are not disabled, and children can receive survivor benefits up to age 19 if they are still in primary or secondary school (Social Security Administration, 2019).[29] Thus, to identify the SSDI population, this study includes individuals who are between the ages of 20-59 with positive Social Security income.[30]

[29] A small group of people can receive Social Security income before age 60 without being disabled. These are spouses, widows, and widowers of Social Security beneficiaries who are taking care of children that are either younger than age 16 or are disabled. In 2009, there were approximately 0.2 million people receiving Social Security income based on this criteria, compared to the approximately 6.4 million people under age 60 receiving Social Security income because of disability (Social Security Administration, 2010). Because of the small size of this group, I am not concerned that their inclusion influences the empirical results.
[30] There is a separate question asking respondents how much Supplemental Security Income they receive; there is an additional question that asks whether the Supplemental Security Income is received because of a disability. There might be concern that individuals do not correctly attribute their income between Social Security and Supplemental Security Income. To test how sensitive the results might be, I produce two separate sets of results based on respondents' answers to these questions. The results are largely robust to these alternative specifications (see robustness checks in Subsection 2.5.4)).

To control for differences in demographics, I use the following variables: age, educational attainment (indicator variables for GED or high school diploma, some college, and bachelors degree or higher), marital status (indicator variables for widowed, divorced, separated, and never married), race/ethnicity (indicator variables for Black non-Hispanic, Hispanic, and other non-White), individual's sex (indicator variable if female), metropolitan statistical area (MSA) status (indicator variable if person resides in an MSA), and household income (indicator variables for household income deciles).[31,32] I also include census region unemployment rates by year (U.S. Bureau of Labor Statistics, 2021) in the analysis. For the prescription drug expenditures and household income amounts, I adjust the values to be in 2007 dollars.[33]

2.4 Methods

2.4.1 Identification Strategy

The main empirical approach used in my analysis is difference-in-differences estimation, with the differences coming from time and Medicare eligibility. Regarding time, the pre-period includes the years before Medicare Part D went into effect (2002-2005) and the post-period includes the years after (2006-2009). Regarding Medicare eligibility, new SSDI beneficiaries become eligible for Medicare after an initial 24-month waiting period. I define the treatment group to be SSDI beneficiaries who have completed the 24-month waiting period and the control

[31] The omitted group is less than GED or high school diploma, married, White non-Hispanic, male, resides outside an MSA, and household income in the first decile.
[32] Because some low-income SSDI beneficiaries will have Medicaid coverage, I expect variation in the outcome variables to be nonlinear with respect to income. This motivates the use of income deciles rather than income as a continuous variable. I use household income rather than personal income because household income determines eligibility for Medicaid. As robustness checks, I test different specifications of controlling for household income. The results are robust to the various specifications (see robustness checks in Subsection 2.5.4).
[33] As a robustness check, I also produce estimates where the drug expenditure amounts are adjusted using medical care CPI, with a base year of 2007. The estimates are robust to this alternative specification (see robustness checks in Subsection 2.5.4).

group to be SSDI beneficiaries still in the 24-month waiting period.[34,35] (Figure B1 depicts the timing of Medicare eligibility as it relates to my identification strategy.) Given that both the treatment and control groups are composed of individuals who are SSDI beneficiaries, I assume they have similar demand for prescription drug insurance coverage.

To understand the effects of Medicare Part D, I estimate its effect on prescription drug coverage, annual prescription drug utilization, and annual prescription drug expenditures. For prescription drug coverage, I evaluate its effect on having any prescription drug coverage (a binary indicator for having public, private, or both types of prescription drug coverage), public drug coverage (a binary indicator for having public drug coverage), and private drug coverage (a binary indicator for having private drug coverage). For prescription drug utilization, I look at individuals' annual number of prescriptions, which includes initial fills and refills. For prescription drug expenditures, I look at individuals' annual total drug expenditure (from all sources), annual public insurance drug expenditure, annual private insurance drug expenditure, and annual out-of-pocket (OOP) drug expenditure.

When Medicare Part D started, Medicaid beneficiaries who were also eligible for Medicare ("dual-eligibles") were required to enroll in Medicare Part D to receive prescription drug insurance, and those who did not select a Part D plan were automatically enrolled into one (Levinson, 2006). Accordingly, to avoid any issues in measuring changes in drug coverage or

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[34] I do not observe how long an individual has received SSDI benefits, only whether they have some Medicare coverage. I designate someone as having completed the 24-month waiting period if I observe their enrollment in at least one Part of Medicare; otherwise, I designate them as not having completed the 24-month waiting period.

[35] Two groups are not subject to the 24-month waiting period: SSDI beneficiaries diagnosed with either ESRD or amyotrophic lateral sclerosis (ALS). They are eligible for Medicare benefits before SSDI cash payments begin (Social Security Administration, 2008). To avoid confounding from the ESRD group, I exclude individuals diagnosed with chronic kidney disease (CKD) for the main estimates as that removes anyone diagnosed with ERSD from my sample. However, my results are robust to including individuals diagnosed with CKD (see robustness checks in Subsection 2.5.4). Regarding ALS, there were approximately 12,000 people with ALS in the U.S. as of 2011 (Mehta et al., 2014). Because this group is small and not all individuals diagnosed with ALS qualify for SSDI, I am not concerned that their potential presence in my sample influences the empirical results.

expenditure, I focus my analysis more broadly on "public" drug coverage and expenditure. I define public drug coverage as coverage under Medicare Part D, MA plans with drug coverage, or Medicaid; public drug expenditures are expenditures associated with these plans. Private drug coverage is defined as coverage from any other sources; private insurance drug expenditures are expenditures associated with these plans.[36]

2.4.2 Econometric Model

To estimate the effect of Medicare Part D on the outcomes of interest, I use the following model:

$$y_{irt} = \beta_0 + \beta_1 Treat_{it} + \beta_2 Treat_{it} \times Post_t + \mathbf{X}'_{irt}\gamma + \theta_r + \lambda_t + \varepsilon_{irt} \quad (2.1)$$

where y_{irt} is the outcome of interest for individual i in year t in census region r, $Treat_{it}$ is 1 if individual i is eligible for Medicare in year t, $Post_t$ is 1 if year t is greater than 2005, $\mathbf{X}_{irt}$ is a vector of controls (demographics and regional unemployment rate), θ_r represents census region fixed effects, λ_t represents year fixed effects, and ε_{irt} is the error term.[37] For the prescription drug coverage outcomes, y_{irt} is 1 if the individual has the applicable prescription drug coverage type and 0 otherwise, so I estimate linear probability models (LPM) for these outcomes.[38] For

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[36] Prior to Medicare Part D, Medigap and MA plans that included prescription drug insurance coverage could be considered public or private drug coverage. Medigap plans were offered by private insurers but were regulated by government agencies. However, the plans were not subsidized by the government and they constituted additional benefits beyond the government plan, so I consider them private coverage. MA plans were offered by private insurers, and the prescription drug coverage they offered prior to Medicare Part D did not have an equivalent public offering. However, these benefits were subsidized by the government, similar to Part D plans, so I consider them public coverage.

[37] $Post_t$ is not separately included in the equation because it is perfectly collinear with the year fixed effects.

[38] Under an LPM, the predicted probabilities can fall outside the [0,1] interval. This can cause ordinary least squares estimates from an LPM to be biased and inconsistent (Horrace & Oaxaca, 2006). To see whether this is a concern, I compare predicted probabilities from LPMs with predicted probabilities from similar probit and logit models. The results are in Figures B2 and B3. Because some predicted probabilities fall outside the [0,1] interval when an LPM is used, I estimate marginal effects for these outcomes under probit and logit models as a robustness check. The results for public coverage and private coverage are robust to these alternative specifications. The any coverage outcome, however, suggests much larger coverage gains from the estimates under the probit and logit models. I discuss this further in Subsection 2.5.4.

the utilization outcome, y_{irt} is individual i's number of prescription drug fills in year t.[39] I one-way cluster standard errors by household and Medicare eligibility status (eligible for Medicare and not eligible for Medicare). For equation (2.1), the coefficient of interest is β_2, which measures the effect of being eligible for Medicare Part D in the post-period on prescription drug coverage, utilization, and expenditures.[40]

This approach implies that I estimate an intent-to-treat (ITT) effect for the utilization and expenditures outcomes of interest. Some would argue that the more relevant effect to estimate is a local average treatment effect (LATE), which would account for individuals who already had public drug coverage before the policy went into effect and individuals who did not take-up public drug coverage after the policy went into effect. However, there is an issue with estimating a LATE for this policy. Since all dual-eligible recipients would have switched from Medicaid prescription drug plans to Medicare Part D plans, any changes in utilization or expenditures brought on by this switch would not be attributed to these switchers if a LATE was estimated. Instead, changes for these individuals would be attributed to the individuals who gained public drug coverage. Thus, estimates of a LATE could be biased. This would be of little importance if only a small group of SSDI beneficiaries had Medicaid coverage, but this does not seem to be the case. Estimates in Table 15 (discussed below) suggest that approximately 49-50 percent of Medicare-eligible SSDI beneficiaries had Medicaid coverage during the study period.

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[39] For utilization, I estimate the model given by equation (2.1) with ordinary least squares; this gives the main estimate for the utilization outcome. As robustness checks, I also estimate count data models. The marginal effects estimates are robust to the alternative specifications (see robustness checks in Subsection 2.5.4).

[40] Although the MEPS includes person-level sampling weights, I forgo using them because I am interested in estimating causal effects instead of population descriptive statistics. When estimating causal effects, one should only use weighted estimation for specific reasons - when estimating a (correctly specified) linear model, weighted least squares (WLS) and ordinary least squares (OLS) both give consistent estimates, but OLS will likely provide more precise estimates (Solon et al., 2015). As a robustness check, I compute WLS estimates. The results are similar for most outcomes, with the exception of total expenditure and public expenditure, which are larger when weighted estimation is done. I discuss this further in Subsection 2.5.4.

2.4.3 *Trend Graphs and Event Study*

To understand the year-to-year effects of the policy, I produce trend graphs for each outcome and estimate an event study model for each outcome. Additionally, in using a difference-in-differences model, I assume parallel trends between the control and treatment groups from the pre-period to the post-period in absence of the treatment; I indirectly test this assumption with the trend graphs and event study estimates.[41] I specify the following event study model:

$$y_{irt} = \alpha_0 + \alpha_1 Treat_{it} + \sum_{\substack{\tau=2002 \\ \tau\neq 2005}}^{2009} \alpha_\tau Treat_{it} \times \mathbb{1}(t=\tau) + \mathbf{X}'_{irt}\delta + \theta_r + \lambda_t + v_{irt} \quad (2.2)$$

where $\mathbb{1}(t=\tau)$ is an indicator function for whether the year of the observation is equal to the year being evaluated. The other variables are defined the same as in equation (2.1). The year 2005 is the reference year, so it is excluded from the event study. I one-way cluster standard errors by household and Medicare eligibility status (eligible for Medicare and not eligible for Medicare).

If the trend graphs show little in the way of pre-reform trends, this would provide suggestive evidence for the parallel trends assumption. For the event study model, the coefficients of interest are α_{2002}, α_{2003}, α_{2004}, α_{2006}, α_{2007}, α_{2008}, and α_{2009}. The coefficients associated with the post-reform period can shed light on how the policy affected each outcome over time. The coefficients associated with the pre-reform period can be used to indirectly test the parallel trends assumption; if the coefficient estimates are not statistically significant, this can provide suggestive evidence for the parallel trends assumption. Additionally, I jointly test that all

[41] A recent literature documents how event study estimates may be problematic for pre-trends testing (see Roth (2022)). I choose to include event study estimates to provide additional, albeit imperfect, support for the parallel trends assumption, but to also estimate the year-to-year effects of the policy.

three pre-2006 coefficient estimates equal 0. A p-value greater than 0.10 would mean that I cannot reject the null hypothesis that all terms equal 0. This would also provide suggestive evidence for the parallel trends assumption.

2.5 Results

2.5.1 Summary Statistics and Trend Graphs

Table 15 shows sample means and standard deviations for the outcomes of interest and select control variables. Columns (1)-(4) show the statistics split by the control and treatment groups, before and after the policy. Column (5) gives unadjusted difference-in-differences estimates based on the sample means. In addition, Figures B4 and B5 show the trends in the sample means for the outcomes of interest split between the control and treatment groups.

For the outcome variables, the sample means imply similar levels of total prescription drug coverage between the control and treatment groups before the reform. They also imply that the treatment group had higher levels of public coverage and lower levels of private coverage. These magnitudes seem reasonable given the lower income levels and the lower marital rate among the treatment group. The sample means for utilization and expenditure suggest higher levels for the treatment group before the reform, except for private insurance expenditure which is similar between both groups.

The unadjusted difference-in-differences results in Table 15, column (5) imply increases in total drug coverage (16.8 percentage points) and public drug coverage (25.2 percentage points), while private coverage decreased (4.6 percentage points). This suggests that SSDI beneficiaries eligible for Medicare Part D saw increased total coverage and a modest decrease in private coverage. This increase in coverage coincided with modest increases in utilization (2 fills) and total drug expenditure ($289), while private insurance drug expenditure had little

Table 15. Summary Statistics - Sample Means by Medicare Eligibility and Period

Variable	Control Group		Treatment Group		DID
	Non-Medicare-eligible before Part D (1)	Non-Medicare-eligible after Part D (2)	Medicare-eligible before Part D (3)	Medicare-eligible after Part D (4)	[(4)-(3)] – [(2)-(1)] (5)
Prescription Drug Coverage					
Any prescription drug coverage	0.699	0.745**	0.719	0.933^^^	0.168‡‡‡
	(0.459)	(0.436)	(0.450)	(0.251)	(0.027)
Public coverage	0.333	0.364	0.565+++	0.848^^^	0.252‡‡‡
	(0.471)	(0.481)	(0.496)	(0.359)	(0.031)
Private coverage	0.384	0.430**	0.208+++	0.208	-0.046
	(0.487)	(0.495)	(0.406)	(0.406)	(0.030)
Both public and private coverage	0.018	0.048***	0.053+++	0.123^^^	0.040‡‡
	(0.134)	(0.215)	(0.225)	(0.329)	(0.016)
Only public coverage	0.315	0.315	0.511+++	0.725^^^	0.214‡‡‡
	(0.465)	(0.465)	(0.500)	(0.447)	(0.032)
Only private coverage	0.366	0.381	0.154+++	0.085^^^	-0.084‡‡‡
	(0.482)	(0.486)	(0.361)	(0.279)	(0.027)
Medicaid coverage	0.333	0.364	0.497+++	0.488	-0.040
	(0.471)	(0.481)	(0.500)	(0.500)	(0.034)
Annual Utilization					
Number of prescriptions (initial fills and refills)	22	24	43+++	47^^	2
	(33)	(35)	(42)	(43)	(2.77)
Annual Expenditure (in 2007 dollars)					
Total prescription drug expenditure	1,588	1,959**	3,523+++	4,183^^	289
	(2,861)	(4,712)	(5,513)	(6,093)	(341)
Public prescription drug expenditure	554	952***	1,766+++	2,931^^^	767‡‡‡
	(1,565)	(3,886)	(4,626)	(4,627)	(268)
Private insurance prescription drug expenditure	492	618*	505	646	15
	(1,753)	(1,909)	(1,823)	(3,768)	(164)
Out-of-pocket prescription drug expenditure	542	389***	1,252+++	606^^^	-493‡‡‡
	(1,226)	(1,140)	(2,360)	(1,282)	(107)

Table 15. Summary Statistics - Sample Means by Medicare Eligibility and Period (continued)

Variable	Control Group: Non-Medicare-eligible before Part D (1)	Control Group: Non-Medicare-eligible after Part D (2)	Treatment Group: Medicare-eligible before Part D (3)	Treatment Group: Medicare-eligible after Part D (4)	DID [(4)-(3)] – [(2)-(1)] (5)
Select Control Variables					
Age (in years)	46.395	46.097	48.596+++	49.078	0.78
	(10.309)	(10.942)	(8.209)	(8.202)	(0.652)
Married	0.457	0.433	0.291+++	0.285	0.018
	(0.498)	(0.496)	(0.455)	(0.451)	(0.034)
Female	0.625	0.650	0.468+++	0.499	0.006
	(0.484)	(0.477)	(0.499)	(0.500)	(0.034)
No GED/HS diploma	0.285	0.271	0.337+++	0.293^^	-0.03
	(0.452)	(0.445)	(0.473)	(0.455)	(0.033)
GED/HS diploma, no college	0.417	0.399	0.410	0.410	0.018
	(0.493)	(0.490)	(0.492)	(0.492)	(0.035)
GED/HS diploma, some college	0.177	0.210**	0.179	0.231^^^	0.019
	(0.382)	(0.408)	(0.384)	(0.422)	(0.029)
Bachelors degree or higher	0.121	0.120	0.073+++	0.066	-0.006
	(0.326)	(0.325)	(0.260)	(0.249)	(0.021)
Race/ethnicity is White, Non-Hisp.	0.525	0.503	0.612+++	0.579	-0.011
	(0.500)	(0.500)	(0.488)	(0.494)	(0.036)
Race/ethnicity is Black, Non-Hisp.	0.240	0.264	0.220	0.269^^	0.025
	(0.427)	(0.441)	(0.415)	(0.444)	(0.031)
Race/ethncity is Hispanic	0.171	0.180	0.117+++	0.111	-0.015
	(0.376)	(0.384)	(0.322)	(0.314)	(0.025)
Race/ethnicity is all other	0.064	0.053	0.050	0.041	0.002
	(0.245)	(0.224)	(0.219)	(0.199)	(0.016)
Resides in MSA	0.749	0.811***	0.660+++	0.731^^^	0.009
	(0.434)	(0.392)	(0.474)	(0.444)	(0.032)
Household income (in 2007 dollars)	39,553	38,858	22, 059+++	21,313	-52
	(42,366)	(46,179)	(22,762)	(18,972)	(2,301)
Census region unemployment rate (%)	5.573	6.049***	5.534++	6.083^^^	0.073
	(0.433)	(1.959)	(0.405)	(1.956)	(0.093)
Observations	1,265	1,094	972	966	

Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease. Expenditure and household income amounts are in 2007 dollars. MSA is abbreviation for "metropolitan statistical area." For columns (1)-(4), standard deviations in parentheses. Column (5) shows difference-in-differences estimates for each variable; standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
Tests of significance (sample means) -
Control group, pre- vs post-Part D difference (two-tailed t-test): * p<0.1, ** p<0.05, *** p<0.01
Treatment group, pre- vs post-Part D difference (two-tailed t-test): ^ p<0.1, ^^ p<0.05, ^^^ p<0.01
Pre-Part D, control vs treatment difference (two-tailed t-test): + p<0.1, ++ p<0.05, +++ p<0.01
Tests of significance (DiD estimates) -
‡ p<0.1, ‡‡ p<0.05, ‡‡‡ p<0.01

change (increase of $15). The more significant changes were the increase in public drug expenditure ($767) that replaced a significant amount of OOP drug expenditure (decrease of $493). We get a better sense of the trends in Figures B4 and B5. Each of the graphs show similar trends between the control and treatment groups prior to the reform and a noticeable change for the treatment group in 2006. The summary statistics and the graphs suggest that a formal regression-based difference-in-differences model would be a promising identification strategy. It is worth noting that the control group trends for each outcome seem to be relatively flat during the study period. This would suggest that difference-in-difference estimates should be fairly similar to simple differences for the treatment group over time. I still think it is worth using the difference-in-differences approach as it can provide a more formal causal interpretation rather than using simple differences.

The sample means for the Medicaid coverage variable suggest that a large portion of SSDI beneficiaries had Medicaid coverage. The reported coverage level was higher for the Medicare-eligible SSDI group. As discussed above, Medicare Part D would have affected individuals with Medicaid coverage differently than individuals without Medicaid coverage. Because of the large number of individuals in the sample reporting Medicaid coverage, I estimate equation (2.1) using separate subsamples based on reported Medicaid status. The subsample results are presented after the main estimates are presented.

The sample means for the control variables suggest large differences for marital status, sex, and household income. The treatment group has a lower share of married individuals, a lower share of female individuals, and lower average household income levels. The other control variables suggest smaller differences between the treatment and control groups. These differences motivate the use of these variables as controls in the regression analysis.

When thinking about the 24-month waiting period for Medicare, it seems that many more SSDI beneficiaries should have Medicare coverage than not, as SSDI beneficiaries can receive benefits for many years after the 24-month waiting period. The sample sizes for both the treatment and control groups, though, show slightly more individuals in the control group. I think this is driven by both the sampling process and potential misreporting. Regarding the sampling process, I drop individuals between the ages 60-64, most of which should qualify for Medicare and be in the treatment group. In 2009, approximately 25 percent of all SSDI beneficiaries were between the ages 60-64 (Social Security Administration, 2010). So, when I drop individuals ages 60-64 from the sample, I am dropping many individuals from the treatment group. This would suggest that the similar size of the treatment and control groups seems somewhat reasonable. One may think, however, that the sample size of the treatment group should still be larger than the control group. Some of this might be driven by potential misreporting, which I discuss in Section 2.6.

2.5.2 Effects on Coverage, Utilization, and Expenditures

Table 16 reports OLS estimates based on the main specification of the empirical model given by equation (2.1). Columns (1)-(3) suggest gaining Part D eligibility led to gains in total drug coverage (18.1 percentage points or 25 percent) and public drug coverage (27.7 percentage points or 49 percent) among SSDI beneficiaries and a decrease in private drug coverage (5.7 percentage points or 27 percent).[42]

Column (4) suggests gaining Part D eligibility led to an increase of two prescription drug fills per year (5 percent) among SSDI beneficiaries. However, I cannot reject the null hypothesis

[42] I also produce estimates for the other coverage outcomes shown in Table 15: having both public and private coverage, having only public coverage, and having only private coverage. The results are shown in Table B1.

Table 16. OLS Estimates of Medicare Part D Introduction on Outcomes of Interest

	Prescription Drug Coverage			Annual Utilization	Annual Prescription Drug Expenditure			
Dependent Variable:	Any Coverage	Public Coverage	Private Coverage	Total Utilization	Total Expend.	Public Expend.	Priv. Ins. Expend.	OOP Expend.
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treat_{it} \times Post_t$	0.181***	0.277***	-0.0568**	2.060	280.4	836.5***	-30.52	-525.5***
	(0.0270)	(0.0275)	(0.0260)	(2.652)	(326.2)	(254.9)	(154.6)	(108.8)
Observations	4,297	4,297	4,297	4,297	4,297	4,297	4,297	4,297
Treatment group pre-2006 DV mean	0.719	0.565	0.208	43	3,523	1,766	505	1,252

Notes: OLS estimates for prescription drug coverage, annual utilization, and annual expenditure (in 2007 dollars). The total utilization variable is a count of all prescribed medications purchased during a given year, and it includes initial purchases and refills. Data from the MEPS for years 2002-2009. Includes SSDI population between ages 20-59, excluding people with chronic kidney disease (CKD). Expenditure amounts are in 2007 dollars. Underlying models include year fixed effects, census region fixed effects, and all controls. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

of no effect on prescription drug fills.[43] This is consistent with Chandra et al. (2017) and Nelson et al. (2014), which both estimate little change in prescription drug fills for non-elderly Medicare beneficiaries gaining Part D eligibility.

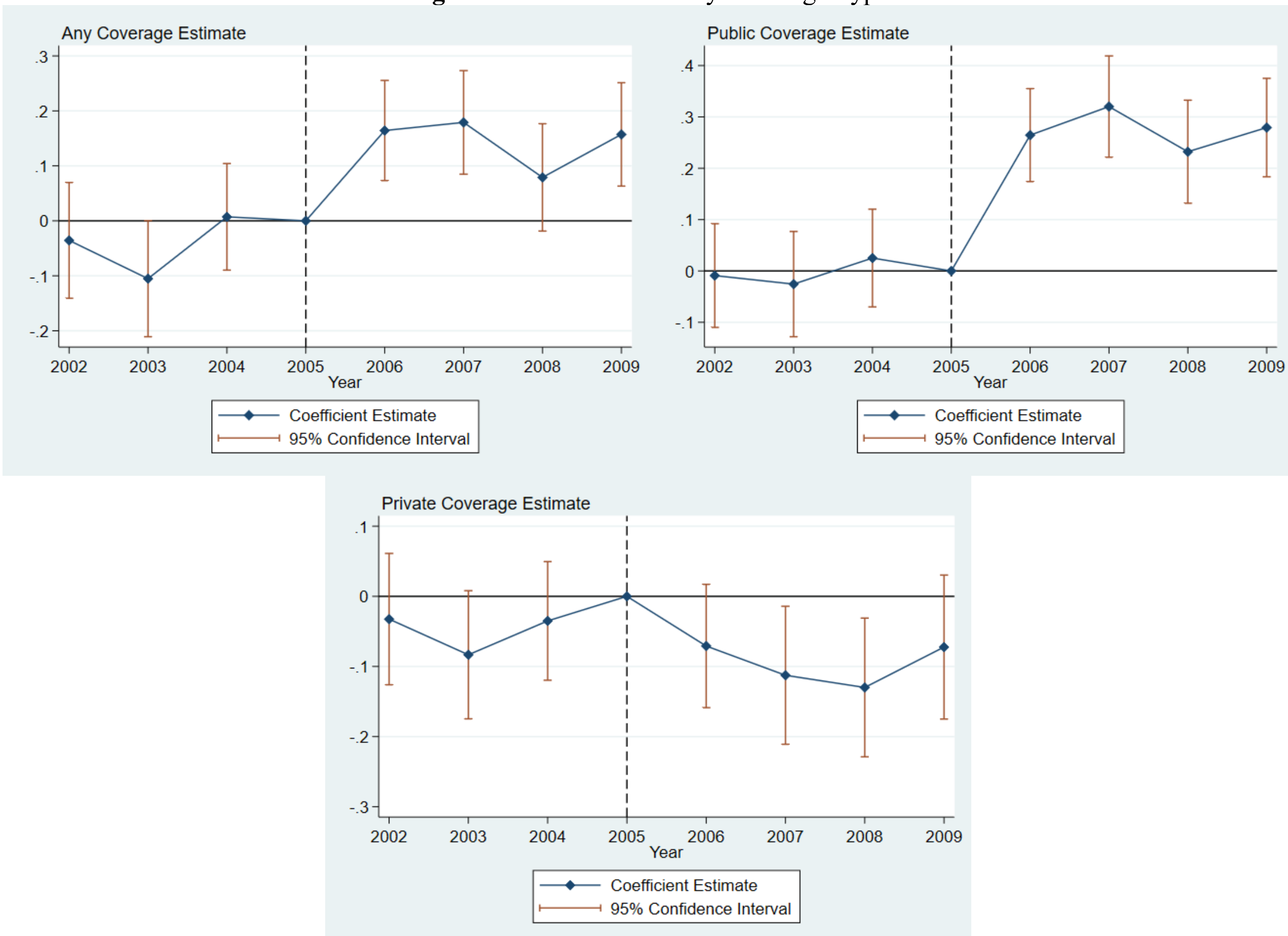
Columns (5)-(8) suggest gaining Part D eligibility led to a $280 increase (8 percent) in total prescription drug expenditure, a $837 increase (47 percent) in public drug expenditure, a $31 decrease (6 percent) in private insurance drug expenditure, and a $526 decrease (42 percent) in OOP drug expenditure among SSDI beneficiaries. The estimated impacts on public drug expenditure and OOP drug expenditure are each statistically significant, while for total drug expenditure and private insurance drug expenditure, I cannot reject the null hypothesis of no effect. The results suggest that gaining Part D eligibility mainly served to shift OOP drug expenditure from SSDI beneficiaries to the federal government with a modest increase in total drug expenditure. Additionally, the estimates suggest that these individuals did not substitute public drug expenditure for private insurance drug expenditure. Because the SSDI population is composed of people with reduced ability to earn labor income, these changes suggest a substantial welfare gain associated with gaining Part D eligibility.

2.5.3 Event Studies

Figures 9-11 plot coefficient estimates from event study regressions for each outcome of interest. The graphs show both the coefficient estimates and 95 percent confidence intervals for each year between 2002 and 2009. The post-reform estimates in Figure 9 are stable from year-to-year. They suggest that take-up of Part D plans took hold right away and stayed fairly consistent

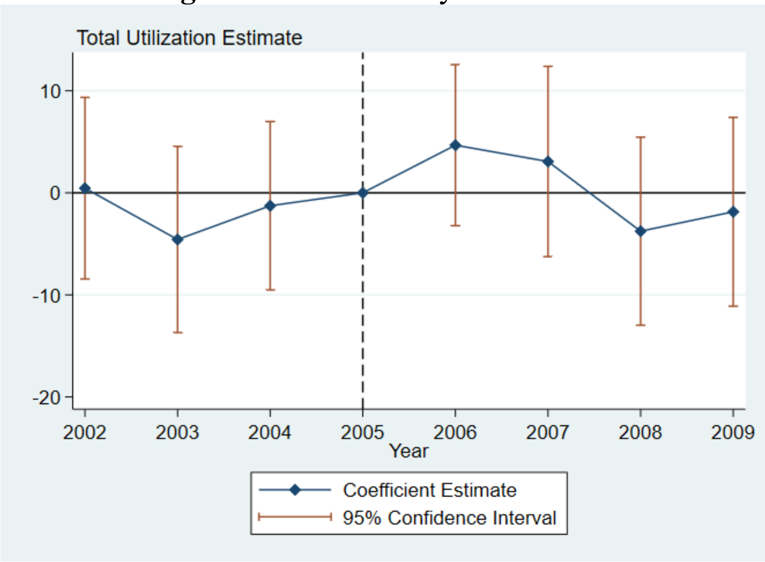
[43] I also examine the changes in utilization of specific prescription drugs. I produce descriptive results of the top five therapeutic subclasses of prescription drugs for each of the difference-in-differences groups (though, I only use the years 2005 and 2006 to avoid occasional changes to drug therapeutic classifications in the MEPS over time). The MEPS prescribed medicines files include this data. The results are in Table B2. The results suggest that there were not any significant changes to utilization of the main therapeutic subclasses of prescription drugs as a result of the policy. In contrast, Asfaw (2019) reports changes in the distribution of prescription drugs by therapeutic class for elderly Medicare beneficiaries.

Figure 9. Event Studies - By Coverage Type



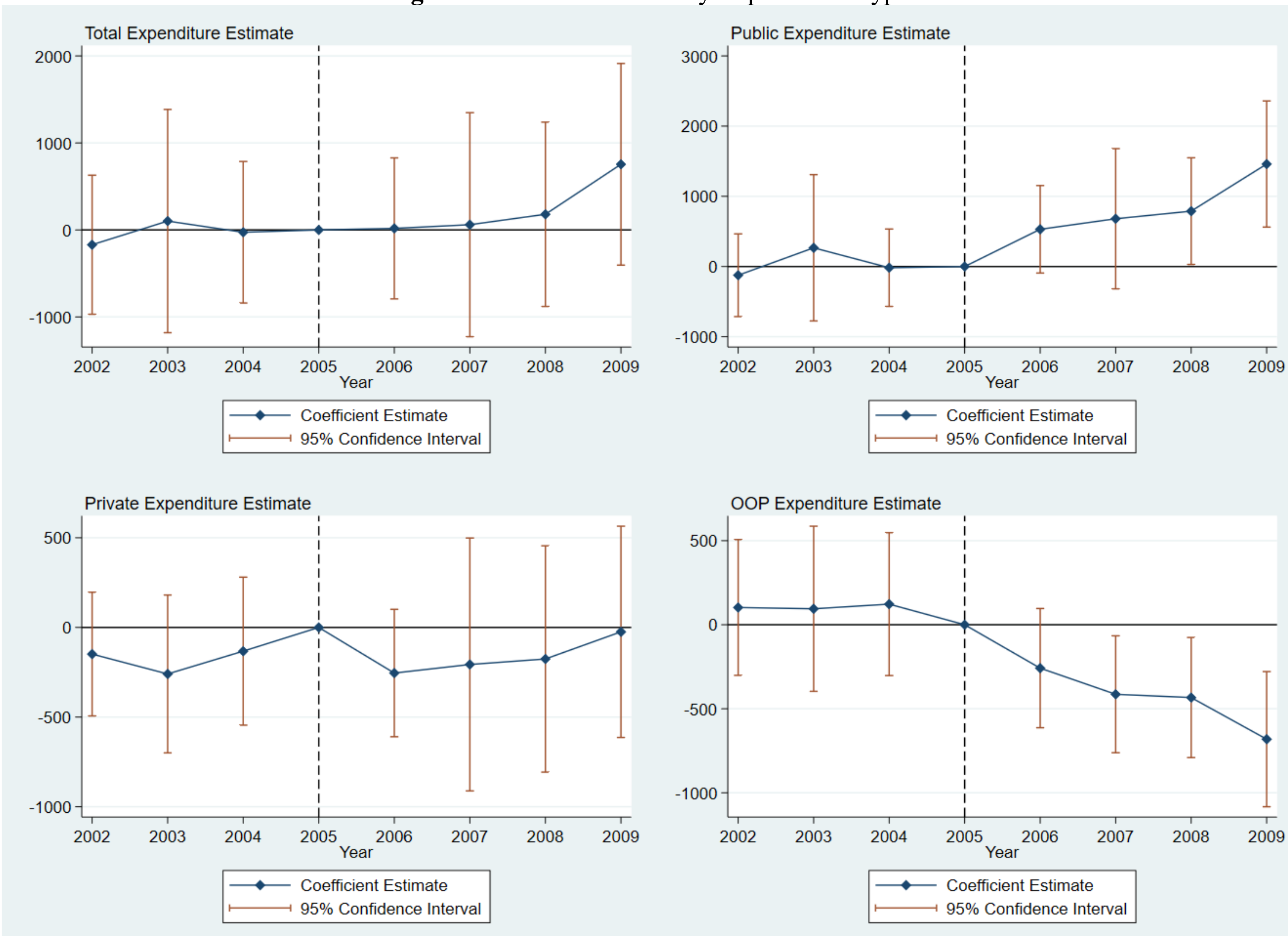
Notes: See Table B3 for notes on regressions used to develop graphs. Base year is 2005.

Figure 10. Event Study - Utilization



Notes: See Table B3 for notes on regressions used to develop graphs. Base year is 2005.

Figure 11. Event Studies - By Expenditure Type



Notes: See Table B3 for notes on regressions used to develop graphs. Base year is 2005.

in the post-reform period. In Figure 10, the post-reform point estimates move from positive to negative. It seems difficult to draw any inference from this figure. Figure 11 suggests that Medicare Part D eligibility had a more gradual impact on expenditure as compared to coverage. This might be expected because, although beneficiaries might have added new coverage right away, it might have taken them some time to fully use their benefits. This is suggested by the upward trend in the post-period seen in the public expenditure graph and the downward trend in the OOP expenditure graph.

None of the graphs have pre-reform coefficient estimates that are significant at the 5 percent level. Additionally, there are no concerning pre-reform trends in any of the graphs. Table B3 reports the associated OLS estimates and F-tests of pre-period coefficient estimates. The p-values from the F-tests are greater than 0.10 for each of the outcomes of interest; thus, for each outcome, I cannot reject the null hypothesis that the pre-reform coefficients jointly equal 0. Each of these results (combined with the discussion of Figures B4 and B5 in Subsection 2.5.1) provides suggestive evidence that the parallel trends assumption holds and that it is reasonable to interpret my difference-in-differences results causally.

2.5.4 Robustness Checks

I examine the robustness of my results to different data, model, and estimation specifications. The results are presented in Tables 17-19. For ease of comparison, Column (1) repeats the baseline estimates from Table 16. Columns (2)-(4) report results from varying the control variables used in the model (as described at the bottom of each column). Variation in which controls are used seems to have no meaningful impact on the results.

Next, in column (5), I report weighted least squares estimates that incorporate the MEPS person-level weights. The results are robust for most outcomes, with the exception of total drug

Table 17. Robustness Checks for Outcomes of Interest

Outcome	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add HH Income Controls (4)	MEPS Person Weights (5)	Probit Model (6)	Logit Model (7)	Include People w/ CKD (8)
Panel 1: Coverage								
Any Coverage	**0.181*** **	0.168***	0.167***	0.180***	0.208***	0.236***	0.254***	0.181***
	(0.0270)	(0.0273)	(0.0272)	(0.0270)	(0.0338)	(0.0289)	(0.0313)	(0.0267)
Public Coverage	**0.277*** **	0.253***	0.264***	0.278***	0.307***	0.274***	0.285***	0.279***
	(0.0275)	(0.0311)	(0.0287)	(0.0275)	(0.0332)	(0.0267)	(0.0274)	(0.0273)
Private Coverage	**-0.0568** **	-0.0451	-0.0576**	-0.0581**	-0.0244	-0.0442*	-0.0487*	-0.0588**
	(0.0260)	(0.0303)	(0.0279)	(0.0260)	(0.0338)	(0.0262)	(0.0266)	(0.0257)
Panel 2: Utilization								
Total Utilization	**2.060**	2.451	2.123	2.190	2.917			1.972
	(2.652)	(2.781)	(2.668)	(2.653)	(3.487)			(2.659)
Panel 3: Expenditure								
Total Expenditure	**280.4**	334.6	312.4	287.3	765.6*			285.9
	(326.2)	(338.5)	(330.3)	(325.9)	(404.0)			(325.0)
Public Expenditure	**836.5*** **	796.0***	815.6***	845.6***	1,304***			855.6***
	(254.9)	(265.0)	(259.1)	(255.0)	(309.5)			(252.4)
Priv. Ins. Expenditure	**-30.52**	25.23	-3.640	-35.01	8.792			-16.08
	(154.6)	(165.1)	(160.5)	(153.8)	(208.4)			(154.2)
OOP Expenditure	**-525.5*** **	-486.5***	-499.5***	-523.3***	-547.0***			-553.6***
	(108.8)	(107.0)	(107.1)	(109.2)	(123.3)			(111.6)
Observations	**4,297**	4,297	4,297	4,297	4,085	4,297	4,297	4,359
Demographics	**Y**		Y	Y	Y	Y	Y	Y
HH Income Deciles	**Y**			Y	Y	Y	Y	Y
Unemployment Rate	**Y**				Y	Y	Y	Y

Notes: Column (1) shows estimates from Table 16. Columns (1)-(4), (8) show OLS estimates of the coefficient of interest in equation (2.1). Column (5) shows weighted least squares estimates for the same coefficient of interest. For panel 1, columns (6)-(7) show marginal effects estimates for the same coefficient of interest. See Table 16 for notes on data used. Column (8) uses same data set but includes people with chronic kidney disease (CKD). Underlying models include year fixed effects and census region fixed effects. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 18. Additional Robustness Checks for Outcomes of Interest

Outcome	Main Estimates (1)	Include if SSI (9)	Exclude if SSI (10)	HH Income Cont. (11)	HH Income Squared (12)	HH Income Quartiles (13)	Poisson Model (14)	Neg. Bin. Model (15)
Panel 1: Coverage								
Any Coverage	**0.181*** **	0.171***	0.223***	0.169***	0.167***	0.180***		
	(0.0270)	(0.0194)	(0.0308)	(0.0272)	(0.0272)	(0.0271)		
Public Coverage	**0.277*** **	0.251***	0.341***	0.261***	0.265***	0.272***		
	(0.0275)	(0.0221)	(0.0300)	(0.0282)	(0.0279)	(0.0275)		
Private Coverage	**-0.0568** **	-0.0560***	-0.0550*	-0.0525**	-0.0579**	-0.0524**		
	(0.0260)	(0.0194)	(0.0301)	(0.0267)	(0.0261)	(0.0260)		
Panel 2: Utilization								
Total Utilization	**2.060**	0.00488	2.646	1.867	1.953	2.000	0.256	0.381
	(2.652)	(2.233)	(2.879)	(2.654)	(2.652)	(2.664)	(2.690)	(2.758)
Panel 3: Expenditure								
Total Expenditure	**280.4**	433.6	434.1	297.2	300.8	278.0		
	(326.2)	(331.2)	(370.6)	(330.1)	(329.8)	(326.9)		
Public Expenditure	**836.5*** **	817.0***	1,054***	796.5***	809.0***	823.5***		
	(254.9)	(236.7)	(276.6)	(258.2)	(257.4)	(253.9)		
Priv. Ins. Expenditure	**-30.52**	80.37	44.07	4.361	-4.566	-18.99		
	(154.6)	(205.6)	(188.7)	(161.1)	(160.7)	(157.1)		
OOP Expenditure	**-525.5*** **	-463.7***	-663.7***	-503.7***	-503.6***	-526.5***		
	(108.8)	(81.05)	(126.7)	(106.7)	(106.8)	(108.6)		
Observations	**4,297**	7,427	3,542	4,297	4,297	4,297	4,297	4,297
Demographics	**Y**	Y	Y	Y	Y	Y	Y	Y
HH Income Deciles	**Y**	Y	Y				Y	Y
Unemployment Rate	**Y**	Y	Y	Y	Y	Y	Y	Y

Notes: Column (1) shows estimates from Table 16. Column (9) uses the original sample plus individuals who report receiving SSI because of a disability. Column (10) uses the original sample but excludes individuals reporting income from SSI. Columns (11)-(13) show estimates under different specifications of the income control variables. Column (11) uses household income as a continuous variable. Column (12) uses household income as a continuous variable and an additional variable for household income squared. Columns (14)-(15) show marginal effects estimates using count data models. Underlying models include year fixed effects and census region fixed effects. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 19. Additional Robustness Checks for Outcomes of Interest

Outcome	Main Estimates (1)	Medical Care CPI (16)	Cluster by Indiv. (17)	Cluster by HH (18)	Two-way Cluster, HH & Age-Year (19)
Panel 1: Coverage					
Any Coverage	**0.181*** **		0.181***	0.181***	0.181***
	(0.0270)		(0.0269)	(0.0270)	(0.0269)
Public Coverage	**0.277*** **		0.277***	0.277***	0.277***
	(0.0275)		(0.0272)	(0.0273)	(0.0280)
Private Coverage	**-0.0568** **		-0.0568**	-0.0568**	-0.0568**
	(0.0260)		(0.0256)	(0.0259)	(0.0262)
Panel 2: Utilization					
Total Utilization	**2.060**		2.060	2.060	2.060
	(2.652)		(2.642)	(2.628)	(2.520)
Panel 3: Expenditure					
Total Expenditure	**280.4**	184.9	280.4	280.4	280.4
	(326.2)	(331.2)	(324.9)	(325.8)	(322.7)
Public Expenditure	**836.5*** **	773.8***	836.5***	836.5***	836.5***
	(254.9)	(258.5)	(254.3)	(254.3)	(242.2)
Priv. Ins. Expenditure	**-30.52**	-34.13	-30.52	-30.52	-30.52
	(154.6)	(155.7)	(154.6)	(154.6)	(166.6)
OOP Expenditure	**-525.5*** **	-554.8***	-525.5***	-525.5***	-525.5***
	(108.8)	(112.1)	(108.5)	(108.7)	(102.8)
Observations	**4,297**	4,297	4,297	4,297	4,297
Demographics	**Y**	Y	Y	Y	Y
HH Income Deciles	**Y**	Y	Y	Y	Y
Unemployment Rate	**Y**	Y	Y	Y	Y

Notes: Column (1) shows estimates from Table 16. In column (16), expenditure amounts are adjusted using medical care CPI, with a base year of 2007. Columns (17)-(19) show estimates under different clustering of errors; for the other columns, standard errors are clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare). Underlying models include year fixed effects and census region fixed effects.
* p<0.1, ** p<0.05, *** p<0.01

expenditure and public drug expenditure. The point estimates from the weighted estimation suggest much larger increases in total drug expenditure and public drug expenditure. However, based on the standard errors, I cannot rule out that the unweighted estimates produce similar magnitudes as the corresponding weighted estimates. I choose to report the unweighted estimates in Table 16 because they are more conservative.

In columns (6)-(7), I report marginal effects estimates from probit and logit models. The results for public coverage and private coverage are robust to these alternative specifications. The any coverage outcome, however, suggests much larger coverage gains from the estimates under the probit and logit models. This might be due to potential bias and inconsistency under the LPM for this outcome (as discussed in Subsection 2.4.2). Given the estimates under these three specifications, I have a fairly broad range of estimates for the any coverage outcome. I choose to report the OLS estimate from the LPM in Table 16 because it is the most conservative estimate.

Column (8) shows estimates when I include individuals diagnosed with chronic kidney disease (CKD). As previously discussed, I exclude individuals diagnosed with CKD from the baseline sample. The estimates in column (8) suggest that the results are robust to their inclusion in the sample.

Columns (9)-(10) show estimates that vary the sample based on whether individuals report receiving Supplemental Security Income (SSI). Column (9) shows estimates that use the original sample plus individuals who report receiving SSI because of a disability. Column (10) shows estimates that use the original sample but excludes individuals who report receiving SSI. The results are robust for most outcomes, with the exception of the any coverage and public coverage outcomes when individuals reporting SSI are excluded. The results for these two outcomes are higher than the main estimates, which makes sense if we are truly excluding individuals receiving SSI. SSDI beneficiaries can also receive SSI benefits; in most states, SSI beneficiaries automatically qualify for Medicaid (Medicaid and CHIP Payment and Access Commission, 2012). Because excluding individuals reporting SSI should primarily exclude individuals with Medicaid coverage, I would expect the group of SSDI beneficiaries not reporting SSI to experience larger increases in any coverage and public coverage.

Columns (11)-(13) show estimates that vary the income control variables. Column (11) shows an estimate where a continuous variable for household income is used instead of the variables for household income deciles. Column (12) shows estimates where a continuous variable for household income and another variable that squares household income are used instead of household income deciles. Column (13) shows estimates where indicator variables for household income quartiles are used instead of the variables for household income deciles. The estimates in columns (11)-(13) suggest that the results are robust to different specifications of controlling for household income.

Columns (14)-(15) show estimates for annual utilization using count data models. Column (14) shows the marginal effects estimate using a Poisson model. Column (15) shows the marginal effects estimate using a negative binomial model. The estimates suggest that the results are robust to the alternative specifications.

Column (16) shows estimates where the drug expenditure amounts are adjusted by medical care CPI, with a base year of 2007. The estimates suggest that the results are robust to the alternative specification.

Columns (17)-(19) show estimates that vary how the standard errors are clustered. Column (17) shows estimates where standard errors are clustered by individual. Column (18) shows estimates where standard errors are clustered by household. Column (19) shows estimates where standard errors are two-way clustered by household and age-year. Standard error estimates under the three alternative specifications are very close to the standard error estimates under the base specification, so the results are robust to these alternative specifications.

2.5.5 Heterogeneity by Medicaid Status

Because of the significant number of individuals in the sample reporting Medicaid coverage, I produce subsample analyses based on reported Medicaid status. I estimate the same model from equation (2.1) using OLS, but I do so separately for each subsample. The results are in Table 20. For ease of comparison, I include the estimates from Table 16 in the first row of estimates. The second row of estimates are based on the subsample of individuals who reported no Medicaid coverage, and the third row of estimates are based on the subsample of individuals who reported having Medicaid coverage.

The estimates based on the subsample of individuals reporting no Medicaid coverage are more easily interpretable; most estimates are statistically significant. The estimates based on the subsample of individuals reporting Medicaid coverage are more difficult to interpret; most estimates are not statistically significant. The estimates suggest very different effects of the policy on individuals with and without Medicaid coverage.

Regarding prescription drug coverage, the estimates suggest that individuals without Medicaid coverage experienced large gains in total drug coverage (36.9 percentage points or 83 percent) and public drug coverage (56.7 percentage points or 420 percent). The estimates suggest only a modest decrease in private coverage (8.40 percentage points or 24 percent). For individuals reporting Medicaid coverage, I only estimate the change in private drug coverage (there will not be any change in any drug coverage or public drug coverage as Medicaid is public

Table 20. Heterogeneity by Medicaid Status

	Prescription Drug Coverage			**Annual Utilization**	**Annual Prescription Drug Expenditure**			
Dependent Variable:	Any Coverage	Public Coverage	Private Coverage	Total Utilization	Total Expend.	Public Expend.	Priv. Ins. Expend.	OOP Expend.
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Entire Sample (N = 4,297)								
$Treat_{it} \times Post_t$	0.181***	0.277***	-0.0568**	2.060	280.4	836.5***	-30.52	-525.5***
	(0.0270)	(0.0275)	(0.0260)	(2.652)	(326.2)	(254.9)	(154.6)	(108.8)
Treatment group pre-2006 DV mean	0.719	0.565	0.208	43	3,523	1,766	505	1,252
Subsample Reporting No Medicaid Coverage (N = 2,524)								
$Treat_{it} \times Post_t$	0.369***	0.567***	-0.0840**	2.808	636.9	1,555***	41.94	-959.6***
	(0.0381)	(0.0283)	(0.0390)	(3.207)	(405.0)	(195.5)	(273.2)	(182.9)
Treatment group pre-2006 DV mean	0.442	0.135	0.343	40	3,157	335	882	1,940
Subsample Reporting Medicaid Coverage (N = 1,773)								
$Treat_{it} \times Post_t$	-	-	-0.0581**	-0.203	-376.2	-202.7	-88.65	-84.86
	-	-	(0.0286)	(4.313)	(543.7)	(503.8)	(98.46)	(91.41)
Treatment group pre-2006 DV mean	1	1	0.070	46	3,894	3,214	123	556

Notes: First row shows estimates from Table 16. The other rows show estimates where the sample is split into observations that reported not having Medicaid coverage (second row of estimates) and observations that reported having Medicaid coverage (third row of estimates). The data, model, and estimation are the same as used for the main estimates in Table 16 (other than splitting the data into subsamples).
* p<0.1, ** p<0.05, *** p<0.01

drug coverage). The estimates suggest that these individuals experienced a modest decrease in private drug coverage relative to the control group (5.81 percentage points or 83 percent).

Regarding prescription drug utilization, the estimates suggest that individuals without Medicaid coverage experienced a modest increase in drug utilization (2.8 prescription drugs fills per year or 7 percent), though the estimate is not statistically significant. For individuals reporting Medicaid coverage, the estimates suggest little change in drug utilization (decrease of 0.203 prescription drugs fills per year or less than 1 percent), though I cannot rule out a modest increase or decrease based on the standard error.

Regarding prescription drug expenditure, the estimates suggest that individuals without Medicaid coverage experienced a $637 increase in total drug expenditure (20 percent), a $1,555 increase in public drug expenditure (464 percent), a $42 increase in private insurance drug expenditure (5 percent), and a $960 decrease in OOP drug expenditure (49 percent). The estimated impacts on public drug expenditure and OOP drug expenditure are statistically significant at the 1 percent level, while for total drug expenditure and private insurance drug expenditure, the estimates are not statistically significant. For individuals reporting Medicaid coverage, the estimates suggest a $376 decrease in total drug expenditure (10 percent), a $203 decrease in public drug expenditure (6 percent), an $89 decrease in private insurance drug expenditure (72 percent), and an $85 decrease in OOP drug expenditure (15 percent). These estimates are not statistically significant.

The results suggest that the overall estimates are driven by the subsample of Medicare-eligible SSDI beneficiaries reporting no Medicaid coverage. Relative to reported dual-eligibles, Medicare-eligible SSDI beneficiaries reporting no Medicaid coverage had significantly lower rates of prescription drug coverage before the policy. We would expect, therefore, that they would experience a much larger increase in drug coverage as a result of the policy. The results bear that out. Consequently, the estimates suggest that Medicare-eligible SSDI beneficiaries without Medicaid coverage experienced a large increase in public drug expenditure and a large decrease in OOP drug expenditure. For reported dual-eligibles, the estimates suggest that they experienced a decrease in spending in all areas of prescription drug expenditure, which could be from the shift of these individuals to Part D plans. The results are not, however, statistically significant, so it is difficult to draw any conclusions.

2.6 Discussion

In this study, I present new evidence about the effects of Medicare Part D on prescription drug coverage, utilization, and expenditures among SSDI beneficiaries. I find that Medicare Part D eligibility led to increased prescription drug coverage (18.1 percentage points or 25 percent), increased public drug coverage (27.7 percentage points or 49 percent), and decreased private drug coverage (5.7 percentage points or 27 percent) among SSDI beneficiaries. Additionally, I find increases in utilization (two prescription drug fills or 5 percent), total drug expenditure ($280 or 8 percent), and public drug expenditure ($837 or 47 percent) among SSDI beneficiaries. The increase in public drug expenditure replaced a significant amount of OOP drug expenditure ($526 decrease or 42 percent) but replaced little private insurance drug expenditure ($31 decrease or 6 percent).

These results suggest that significantly more SSDI beneficiaries gained drug coverage (18.1 percentage points) then replaced private drug coverage (5.7 percentage points) after becoming eligible for Medicare Part D. That being said, the percent changes were similar for gains in drug coverage (25 percent) and decreases in private drug coverage (27 percent). This merely reflects the smaller number of Part D eligible SSDI beneficiaries who had private coverage prior to the reform (21 percent) relative to total drug coverage (72 percent).

The expenditures results are somewhat consistent with Nelson et al. (2014), which estimates a large decrease in OOP drug expenditure (55 percent) among non-elderly Medicare beneficiaries gaining Part D eligibility. However, they also estimate a large decrease in private insurance drug expenditure (63 percent). I use a different identification strategy than they do, which may be driving the difference in results. Their study uses difference-in-differences estimation and a similar treatment group as my study, but for their control group, they use propensity score matching to identify other individuals under age 65 with similar characteristics as their treatment group. Of course, propensity score matching matches individuals based on observable characteristics; I think SSDI beneficiaries waiting for Part D eligibility may serve as a better control group for SSDI beneficiaries with Part D eligibility because these two groups are more likely to share similar unobservable characteristics.

Regarding total drug expenditure, my results are inconsistent with Chandra et al. (2017), which estimates a large increase ($944). I use a different estimation strategy, which may be driving the difference in results. The authors use difference-in-differences estimation and a similar treatment group as my study, but for their control group, they use individuals ages 18-64 with private health insurance coverage. Individuals in their control group could be fairly different than SSDI beneficiaries. Similarly argued in the previous paragraph, I think SSDI beneficiaries waiting for Part D eligibility may serve as a better control group for SSDI beneficiaries with Part D eligibility because these two groups are more likely to share similar unobservable characteristics. Another difference in estimation is that the authors use the MEPS survey weights. When I use the MEPS survey weights, I get a much larger estimate for total drug expenditure ($766 increase) with a fairly large standard error. This estimate is more consistent with the estimate from Chandra et al. (2017).

For the elderly population, Engelhardt and Gruber (2011) estimate a 10 percentage point increase (14 percent increase from the pre-reform mean) in total drug coverage and a 40 percentage point increase (154 percent increase from the pre-reform mean) in public drug coverage. They do not report an estimate for the change in private drug coverage, so I replicate their paper and estimate an 11 percentage point decrease (21 percent decrease from the pre-reform mean).[44] My estimates suggest that the SSDI population saw a much larger increase in total prescription drug coverage, a smaller increase in public drug coverage, and a smaller decrease in private drug coverage (in percentage point terms). Altogether, this suggests greater welfare gains for the SSDI population compared to the elderly population.

Turning to annual prescription drug expenditures, estimates for both the elderly and SSDI populations suggest that the policy caused large increases in public expenditure and large decreases in OOP expenditure.[45] However, the estimates for the elderly population suggest large decreases in private insurance drug expenditure, whereas my estimates for the SSDI population suggest little change in private insurance drug expenditure. Thus, the policy mainly served to reduce OOP expenditure for the SSDI population, whereas for the elderly population, it reduced some OOP expenditure but also caused substitution away from private insurance drug expenditure. This suggests larger welfare gains for the SSDI population.

With any public insurance expansion, there is the potential for crowd-out (see Gruber and Simon (2008)). Although it seems there was some crowd-out of SSDI private prescription drug

[44] My replication results of Engelhardt and Gruber (2011) are in Appendix C. My replication results are consistent with the results in Engelhardt and Gruber's paper.

[45] As previously mentioned, Engelhardt and Gruber (2011) estimate a local average treatment effect for drug utilization and expenditures, whereas I estimate an intent-to-treat effect. As such, I can only make qualitative comparisons to their estimated effects for these outcomes.

coverage because of Medicare Part D's introduction, it does not seem significant. As already discussed, public drug coverage and public drug expenditure both increased significantly, but private drug coverage and private insurance drug expenditure decreased modestly. This suggests modest crowd-out from the policy for the SSDI population. For the elderly population, though, crowd-out was more significant (Engelhardt & Gruber, 2011; Levy & Weir, 2010; Lichtenberg & Sun, 2007). The studies find large decreases in private drug coverage, private insurance drug expenditure, and utilization associated with private drug coverage.

This discussion highlights why we should study the heterogeneous effects of Medicare policy across the different populations the program serves. Most research regarding Medicare Part D (as well as other areas of Medicare) has focused on the elderly population, leaving a gap in our knowledge regarding its effects on the SSDI population. The results of this study fill some of that gap.

From a public finance perspective, we also have reason to study the effects of Medicare policy on the SSDI population. As of 2014, Medicare costs for the under age 65 population ($13,098 per beneficiary) were 31 percent higher than costs for the elderly population ($9,972 per beneficiary) (Cubanski et al., 2016).[46] This was driven by especially higher Part D costs per beneficiary of $3,817 for the under age 65 population relative to $1,159 for the elderly population (329 percent higher). For policymakers to understand the budgetary consequences of any Medicare policy, especially policy for prescription drugs, it is important to study their effect on SSDI beneficiaries.

This study is not without limitations. First, this study relies on quasi-random variation because Medicare eligibility was not randomly assigned. Though, the control group selected was

[46] The data used to produce these figures excludes beneficiaries in Medicare Advantage plans.

meant to serve as an appropriate counterfactual to the treatment group so that it was “as if” eligibility was randomly assigned. Second, part of the post-reform period in the study includes the Great Recession. The Great Recession led to significant changes in the employment landscape affecting individuals' decisions to apply for SSDI. The region and year fixed effects in the difference-in-differences model, as well as the use of unemployment rates as a control, should help control for some effects from the Great Recession. Additionally, given the immediacy of take up of Part D benefits and the similar level of coverage throughout the post-reform period (as indicated by the event study results), I have confidence that the empirical strategy does an adequate job controlling for the Great Recession's effects.

If application for SSDI benefits is endogenous, there might be concern that the introduction of prescription drug benefits to the Medicare program may have incentivized some individuals to apply for SSDI benefits. If these newly incentivized applicants were different than typical applicants to the SSDI program, then the composition of the SSDI population might have changed as a result of the policy; this could pose a threat to the parallel trends assumption of the difference-in-differences framework. My event study results assuage such concerns due to the lack of differential trends in the pre-reform period.

Potential misreporting might also be of concern for the study. Individuals might misreport their SSDI income as income from SSI (or vice-versa). As robustness checks, I altered the sample based on whether the individual did or did not report income from SSI and then produced estimates for the main outcomes of interest. The results are largely robust to the alternative sample definitions (I discuss this further in Subsection 2.5.4), so I am less concerned about this potential misreporting. Individuals may also misreport their insurance coverage types. If individuals misreport their Medicare coverage status, then I may incorrectly classify whether individuals should be in the treatment or control group. This may explain why more individuals are in the control group relative to the treatment group in Table 15; the likely case is individuals having Medicare coverage but not reporting it, which means they should be classified in the treatment group but are instead classified in the control group. Given I cannot confirm whether individuals are misreporting Medicare coverage, this remains a limitation of the study.

The statistics in Table 15 suggest that SSDI individuals not eligible for Part D lag behind in prescription drug coverage. This suggests that the Medicare waiting period may be a barrier to accessing prescription drug coverage for this vulnerable population. Thus, it would be worthwhile to evaluate potential policy remedies. One policy that might have increased coverage for this group was the ACA. The ACA extended Medicaid coverage to many individuals. Although some disabled individuals qualified for Medicaid before the ACA, the income limit was on average much lower for disabled individuals (87 percent of the federal poverty level) than the income limit established by the ACA (138 percent) (Wagner, 2015). Additionally, in the individual health insurance markets, the ACA disallowed pre-existing condition exclusions, imposed community rating, and implemented premium subsidies for individuals with low incomes. These changes could have improved health insurance access for SSDI individuals in the Medicare waiting period. I am not aware of any study that has looked into this. Another policy option would be to eliminate the Medicare waiting period altogether, which has been considered by policymakers.[47] The results of this paper may provide evidence regarding the effects of such a policy.

[47] Recently proposed legislation includes the Ending the Medicare Disability Waiting Period Act of 2005 (2005) and the Stop the Wait Act (2019).

CHAPTER 3: Evaluating Heterogeneous Effects and Health-Related Outcomes of Medicare Part D on SSDI Medicare Beneficiaries

3.1 Introduction

The Medicare program added prescription drug benefits in 2006. Although some Medicare beneficiaries had prescription drug coverage prior to the reform (e.g., from Medigap coverage), millions lacked coverage (Duggan et al., 2008). One group that stood to benefit was Social Security Disability Insurance (SSDI) beneficiaries eligible for Medicare. SSDI beneficiaries qualify for Medicare coverage after a two-year waiting period.

A limited literature has studied the effects of Medicare Part D on the Medicare-eligible SSDI population. These studies find large increases in prescription drug coverage (Alfrey, Forthcoming), mixed evidence of an increase in prescription drug expenditure (Alfrey, Forthcoming; Chandra et al., 2017; Nelson et al., 2014), and little to no change in prescription drug utilization (Alfrey, Forthcoming; Chandra et al., 2017; Nelson et al., 2014).

Of the studies investigating the effects of Medicare Part D on SSDI beneficiaries, Chandra et al. (2017) and Nelson et al. (2014) study the effect of the program on inpatient utilization/expenditure, emergency department utilization/expenditure, and physician office visit utilization/expenditure. The studies find mixed results on whether the number of hospitalizations changed. The studies show inconclusive evidence about the effects on inpatient expenditure, emergency department utilization/expenditure, and physician office visit utilization/expenditure; the results are not statistically significant at the 5 percent level for any of these outcomes and the standard errors are large.

I find no studies that evaluate the heterogeneous effects of Medicare Part D on different subgroups of the Medicare-eligible SSDI population. Additionally, I find no studies that evaluate health status outcomes or prescription drug price outcomes in the context of Medicare Part D and the Medicare-eligible SSDI population. This study attempts to fill some of these gaps. Lastly, this study uses a different identification strategy for evaluating the effects of Medicare Part D on non-prescription drug outcomes for SSDI Medicare beneficiaries.

Using difference-in-differences estimation and data from the Medical Expenditure Panel Survey, I study various outcomes related to the introduction of Medicare Part D and the Medicare-eligible SSDI population. Similar to Alfrey (Forthcoming), I compare outcomes for SSDI beneficiaries eligible for Medicare against those not eligible for Medicare. For the Part D eligible population, I estimate that the policy increased drug coverage more for older individuals, individuals with education, men, and married individuals. This led to larger decreases in out-of-pocket drug expenditure for the same subgroups. The estimates also suggest improvements in both perceived health status and perceived mental health status. The estimates regarding non-prescription drug outcomes and prescription drug prices are difficult to draw inference from as most estimates are not statistically significant and because the standard errors are large.

I organize the rest of the paper as follows. In Section 3.2, I discuss the data used for the study. In Section 3.3, I discuss the identification strategy and econometric model used for the study. In Section 3.4, I present the results from the econometric model. In Section 3.5, I discuss the results and conclude the paper.

3.2 Data

I use data from the Medical Expenditure Panel Survey (MEPS). I use the data set in a similar way as Alfrey (Forthcoming), though I look at additional outcomes. The MEPS is a nationally representative survey of the U.S. non-institutionalized population. It has detailed data appropriate for studying various health care-related outcomes. I use data from the years 2002 to

2009. I use the survey answers from the end of each calendar year. I do not use years beyond 2009 to avoid confounding from the Affordable Care Act (ACA). The ACA changed aspects of the Medicare Part D program that affected out-of-pocket drug spending for Part D beneficiaries; the out-of-pocket changes took effect in 2010.

For this study, I investigate the following prescription drug outcomes: any prescription drug coverage; public drug coverage; private drug coverage; total drug utilization; total drug expenditure; total public drug expenditure; total private insurance drug expenditure; and out-of-pocket drug expenditure. For the expenditure amounts, I adjust the values to 2007 dollars.

The MEPS is also appropriate for performing heterogeneity analysis. The MEPS contains various demographic characteristics of survey respondents. I investigate the heterogeneity of prescription drug outcomes based on the following demographic splits: age (ages 20-49 versus ages 50-59), education level (no college versus at least some college), individual's sex (male versus female), and marital status (married versus not married).[48]

I look at the following additional outcomes: total medical expenditure; office-based visit expenditure; total hospital outpatient expenditure; emergency room expenditure; total hospital inpatient expenditure; changes in prescription drugs prices; office-based visit utilization; total hospital outpatient utilization; total emergency room utilization; total inpatient hospital discharges; total number of nights inpatient stay; self-reported health status; and self-reported mental health status. For the expenditure and price amounts, I adjust the values to 2007 dollars.

For the self-reported health status variables, the MEPS asks individuals to rate their perceived health status according to the following categories: excellent, very good, good, fair, and poor. This is done for both perceived overall health status and perceived mental health

[48] For each of the demographic characteristics, I split the sample into two subgroups each because of the small size of the overall sample.

status. The MEPS creates two variables (one for perceived health status and one for perceived mental health status) ranging in values from one to five to line up with the five reportable health status categories. I use both variables for the analysis. For both variables, I further break down a variable into five separate indicator variables for whether the individual reports excellent health status, very good health status, and so on. The subsequent 10 indicator variables (five for self-reported health status and five for self-reported mental health status) serve as the main health status outcomes for the study.

The MEPS can be used to estimate changes in the prices of prescription drugs. Because the MEPS provides prescription drug utilization information and expenditure information, I can estimate the price of each prescription. To develop the price estimate for each individual, I divide the individual's amount of prescription drug expenditure by the individual's number of prescriptions. This gives an average prescription drug price for each individual.

To identify individuals for the study, I use the Social Security income variable in the MEPS. The variable asks how much income a respondent receives from Social Security. Individuals under age 65 can receive SSDI benefits. Additionally, individuals aged 60 and older can receive Social Security income related to survivor benefits if they are not disabled, and children can receive survivor benefits up to age 19 (Social Security Administration, 2019). To identify SSDI individuals, I keep only respondents who report earning Social Security income and are between the ages 20-59; this avoids including individuals who are receiving Social Security survivor or retirement benefits between the ages 60-64 or individuals under age 20 receiving survivor benefits.

For the study, I use the following control variables: age, level of education (indicator variables for if person has GED or high school diploma, some college, or bachelors degree or higher), marital status (indicator variables for if person is widowed, divorced, separated, or never married), race/ethnicity (indicator variables for if person is Black non-Hispanic, Hispanic, or other non-White), individual's sex (indicator variable for if female), metropolitan statistical area (MSA) status (indicator for if person resides in an MSA), income deciles, and census region unemployment rates.[49] For the household income amounts, I adjust the values to be in 2007 dollars. All variables but the unemployment rates are found in the MEPS. The unemployment rates are annual rates from U.S. Bureau of Labor Statistics (2021).

3.3 Methods

3.3.1 Identification Strategy

I use difference-in-differences estimation for the study. I follow the approach from Alfrey (Forthcoming), which studies the same policy and population. For the difference-in-differences estimation, the two differences are Medicare eligibility and time. Regarding Medicare eligibility, I compare SSDI individuals eligible for Medicare (treatment group) against SSDI individuals not eligible for Medicare (control group). Both groups should have similar unobservable characteristics as they are both comprised of individuals with long-term disabilities that preclude substantial gainful employment. The other difference is time: before the reform (2002-2005) and after the reform (2006-2009).

3.3.2 Econometric Model

To estimate the effect of Medicare Part D on the outcomes of interest, I use the following model:

$$y_{irt} = \beta_0 + \beta_1 Treat_{it} + \beta_2 Treat_{it} \times Post_t + \mathbf{X}'_{irt}\gamma + \theta_r + \lambda_t + \varepsilon_{irt} \quad (3.1)$$

where y_{irt} is the outcome of interest for individual i in year t in census region r, $Treat_{it}$ is 1 if

[49] The omitted group is less than GED or high school diploma, married, White non-Hispanic, male, resides outside an MSA, and household income in the first decile.

individual i is eligible for Medicare in year t, $Post_t$ is 1 if year t is greater than 2005, $\mathbf{X}_{irt}$ is a vector of controls (demographics and regional unemployment rate), θ_r represents census region fixed effects, λ_t represents year fixed effects, and ε_{irt} is the error term.[50] I one-way cluster standard errors by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare).

3.3.3 Event Study

To study the year-to-year effects of the policy as well as to indirectly test the parallel trends assumption, I specify the following event study model:

$$y_{irt} = \alpha_0 + \alpha_1 Treat_{it} + \sum_{\substack{\tau=2002 \\ \tau\neq 2005}}^{2009} \alpha_\tau Treat_{it} \times \mathbb{1}(t=\tau) + \mathbf{X}'_{irt}\delta + \theta_r + \lambda_t + \upsilon_{irt} \quad (3.2)$$

where $\mathbb{1}(t=\tau)$ is an indicator function for whether the year of the observation is equal to the year being evaluated. The other variables are defined the same as in equation (3.1). The year 2005 is the reference year, so it is excluded from the event study. I one-way cluster standard errors by household and Medicare eligibility status (eligible for Medicare and not eligible for Medicare).

For the event study model, the coefficients of interest are α_{2002}, α_{2003}, α_{2004}, α_{2006}, α_{2007}, α_{2008}, and α_{2009}. The post-period coefficients can help us understand the post-period dynamics of the policy. The pre-period coefficients can indirectly test the parallel trends assumption; if the coefficient estimates are not statistically significant, this can provide suggestive evidence for the parallel trends assumption.

[50] $Post_t$ is not separately included in the equation because it is perfectly collinear with the year fixed effects.

3.4 Results

3.4.1 Summary Statistics

I develop summary statistics for both the heterogeneity categories and the other outcomes. The tables show sample means for Medicare-eligible SSDI beneficiaries (i.e., the treatment group). Table 21 shows sample means for the prescription drug dependent variables based on the heterogeneity categories. Table 22 shows sample means for the other health care expenditure and utilization variables. Table 23 shows sample means for the self-reported health status variables.

Heterogeneity Categories. In Table 21, columns (1)-(4) shows sample means by age. I split the sample into younger beneficiaries (ages 20-49) and older beneficiaries (ages 50-59). This splits the sample into approximately equal size subsamples. Notice that having any prescription drug coverage was higher for younger beneficiaries relative to older beneficiaries prior to the reform. The age groups had similar coverage after the reform. Also noteworthy, out-of-pocket drug expenditure was much higher for older beneficiaries before the reform, but it decreased to similar levels as younger beneficiaries after the reform.

In Table 21, columns (5)-(8) shows sample means by education level. I split the sample into beneficiaries with no college education (person has either less than GED or high school diploma or person has GED or high school diploma) and beneficiaries with at least some college education (person has either some college or person has bachelors degree or higher). Both subgroups had similar levels of prescription drug coverage before and after the reform. The group with higher education had higher prescription drug expenditure before and after the reform.

Table 21. Summary Statistics - Sample Means of Prescription Drug Outcomes by Heterogeneity Categories (Medicare-eligible SSDI beneficiaries only)

	Age 20-49		**Age 50-59**		**Education: No College**		**Education: At Least Some College**	
Variable	Pre-period (1)	Post-period (2)	Pre-period (3)	Post-period (4)	Pre-period (5)	Post-period (6)	Pre-period (7)	Post-period (8)
Coverage								
Any coverage	0.753	0.930	0.690	0.934	0.717	0.931	0.727	0.937
	(0.432)	(0.255)	(0.463)	(0.248)	(0.451)	(0.254)	(0.447)	(0.243)
Public coverage	0.646	0.870	0.496	0.831	0.593	0.861	0.482	0.815
	(0.479)	(0.336)	(0.500)	(0.375)	(0.492)	(0.346)	(0.501)	(0.389)
Private coverage	0.148	0.161	0.259	0.244	0.168	0.180	0.327	0.275
	(0.355)	(0.368)	(0.438)	(0.430)	(0.374)	(0.384)	(0.470)	(0.447)
Utilization								
Total utilization	35	40	49	53	41	45	50	51
	(40)	(38)	(42)	(45)	(42)	(40)	(41)	(48)
Expenditure								
Total expenditure	3,147	4,028	3,842	4,309	3,237	3,499	4,371	5,816
	(6,807)	(6,256)	(4,088)	(5,972)	(5,564)	(4,229)	(5,279)	(8,893)
Public expenditure	1,937	3,056	1,620	2,842	1,806	2,635	1,646	3,641
	(6,053)	(5,118)	(2,911)	(4,223)	(4,996)	(3,857)	(3,297)	(6,025)
Priv. ins. expenditure	369	424	620	816	300	294	1,115	1,481
	(1,600)	(3,101)	(1,987)	(4,201)	(1,016)	(1,030)	(3,107)	(6,663)
OOP expenditure	840	549	1,602	651	1,131	570	1,611	694
	(1,603)	(1,509)	(2,802)	(1,079)	(2,271)	(1,291)	(2,577)	(1,260)
Observations	446	416	526	549	727	678	245	287

Notes: Data from the MEPS for years 2002-2009. Includes Medicare-eligible SSDI population for ages 20-59, excluding people with chronic kidney disease. Expenditure amounts are in 2007 dollars. Standard deviations in parentheses.

Table 21. Summary Statistics - Sample Means of Prescription Drug Outcomes by Heterogeneity Categories (Medicare-eligible SSDI beneficiaries only) (continued)

	Male		**Female**		**Married**		**Not Married**	
Variable	Pre-period (9)	Post-period (10)	Pre-period (11)	Post-period (12)	Pre-period (13)	Post-period (14)	Pre-period (15)	Post-period (16)
Coverage								
Any coverage	0.683	0.907	0.760	0.959	0.675	0.913	0.737	0.941
	(0.466)	(0.291)	(0.427)	(0.200)	(0.469)	(0.283)	(0.440)	(0.237)
Public coverage	0.497	0.805	0.642	0.890	0.353	0.775	0.652	0.877
	(0.500)	(0.396)	(0.480)	(0.313)	(0.479)	(0.419)	(0.477)	(0.329)
Private coverage	0.259	0.238	0.149	0.178	0.392	0.313	0.132	0.167
	(0.439)	(0.426)	(0.357)	(0.383)	(0.489)	(0.464)	(0.339)	(0.373)
Utilization								
Total utilization	37	39	49	55	49	52	40	45
	(39)	(40)	(44)	(44)	(45)	(43)	(40)	(42)
Expenditure								
Total expenditure	2,923	3,906	4,205	4,471	3,547	4,466	3,513	4,077
	(4,178)	(6,715)	(6,655)	(5,393)	(3,982)	(5,733)	(6,033)	(6,233)
Public expenditure	1,286	2,641	2,310	3,228	964	2,583	2,095	3,074
	(2,889)	(5,103)	(5,976)	(4,083)	(2,307)	(4,187)	(5,258)	(4,789)
Priv. ins. expenditure	606	759	391	535	1,043	1,052	284	486
	(2,159)	(4,247)	(1,337)	(3,221)	(2,636)	(3,406)	(1,294)	(3,896)
OOP expenditure	1,031	505	1,504	708	1,539	831	1,134	517
	(1,812)	(994)	(2,838)	(1,512)	(2,251)	(1,236)	(2,394)	(1,291)
Observations	517	483	455	482	283	275	689	690

Notes: Data from the MEPS for years 2002-2009. Includes Medicare-eligible SSDI population for ages 20-59, excluding people with chronic kidney disease. Expenditure amounts are in 2007 dollars. Standard deviations in parentheses.

Table 22. Summary Statistics - Sample Means of Health Care Expenditure and Utilization Outcomes (Medicare-eligible SSDI beneficiaries only)

Variable	Pre-period (1)	Post-period (2)
Expenditure		
Total medical	10,994.30	12,908.14
	(18,167.26)	(21,975.16)
Office-based visit	1,670.57	1,918.86
	(2,790.88)	(3,749.12)
Hospital outpatient	463.72	836.09
	(1,573.37)	(5,135.51)
Emergency room	280.80	368.94
	(1,110.70)	(1,631.75)
Hospital inpatient	3,241.21	3,443.56
	(10,832.56)	(13,753.95)
Utilization		
Office-based visit	12.48	12.22
	(16.83)	(17.86)
Hospital outpatient	1.12	1.49
	(3.19)	(6.66)
Emergency room	0.52	0.50
	(1.22)	(1.14)
Hospital inp. discharges	0.34	0.33
	(0.80)	(0.85)
Hospital inp. nights	2.61	1.92
	(10.64)	(7.38)
Prescription drug prices		
Price	72.36	88.36
	(74.10)	(144.40)
Observations	972	965

Notes: Data from the MEPS for years 2002-2009. Includes Medicare-eligible SSDI population for ages 20-59, excluding people with chronic kidney disease. Expenditure and price amounts are in 2007 dollars. Standard deviations in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 23. Summary Statistics - Sample Means of Health Status Outcomes (Medicare-eligible SSDI beneficiaries only)

Variable	Pre-Period (1)	Post-Period (2)
Perceived health status		
Health status	0.04	0.05
"Excellent"	(0.20)	(0.21)
Health status	0.09	0.10
"Very good"	(0.28)	(0.29)
Health status	0.25	0.27
"Good"	(0.44)	(0.44)
Health status	0.31	0.37
"Fair"	(0.46)	(0.48)
Health status	0.31	0.22
"Poor"	(0.46)	(0.41)
Health status	0.38	0.41
"Good" or better	(0.49)	(0.49)
Health status	0.13	0.14
"Very good" or better	(0.33)	(0.35)
Perceived mental health status		
Mental health status	0.10	0.12
"Excellent"	(0.29)	(0.32)
Mental health status	0.14	0.15
"Very good"	(0.35)	(0.35)
Mental health status	0.36	0.36
"Good"	(0.48)	(0.48)
Mental health status	0.26	0.29
"Fair"	(0.44)	(0.46)
Mental health status	0.14	0.09
"Poor"	(0.35)	(0.28)
Mental health status	0.60	0.62
"Good" or better	(0.49)	(0.49)
Mental health status	0.23	0.26
"Very good" or better	(0.42)	(0.44)
Observations	972	965

Notes: Data from the MEPS for years 2002-2009. Includes Medicare-eligible SSDI population for ages 20-59, excluding people with chronic kidney disease. Standard deviations in parentheses.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

In Table 21, columns (9)-(12) shows sample means by sex. There was approximately an equal number of men and women in the treated part of the sample. Women had slightly higher levels of prescription drug coverage before and after reform. Women had a larger decrease in out-of-pocket drug expenditure.

In Table 21, columns (13)-(16) shows sample means by marital status. I split the sample into beneficiaries who are married and beneficiaries who are not married. There are more people who are unmarried, but this seemed like the most appropriate split given the potential higher number of health insurance options when married. Married individuals had a very large increase in public coverage. This led to a very large increase in public drug expenditure for married individuals.

Other Health Care Expenditure and Utilization. In Table 22, the first section shows various medical expenditure types, and the second section shows various utilization types. The third section shows average prescription drug prices. Starting with total medical expenditure, there was a slight increase from the pre-period to the post-period. The largest absolute increase was in hospital outpatient expenditure. Regarding utilization, hospital outpatient was the only utilization type to increase from the pre-period to the post-period. Lastly, in Table 22, the average prescription drug price seemed to increase; the standard deviation also increased substantially.

Self-Reported Health Status. In Table 23, the top section shows perceived health status, and the bottom section shows perceived mental health status. Regarding perceived health status, all health statuses but "Poor" showed an increase in the percent of people reporting that status. The status "Fair" showed the largest absolute increase of the four statuses that showed an increase.

For perceived mental health status, only the status “Poor” had a decrease. All other statuses either increased or stayed the same. The largest absolute increase was for the status “Fair.”

3.4.2 Trend Graphs

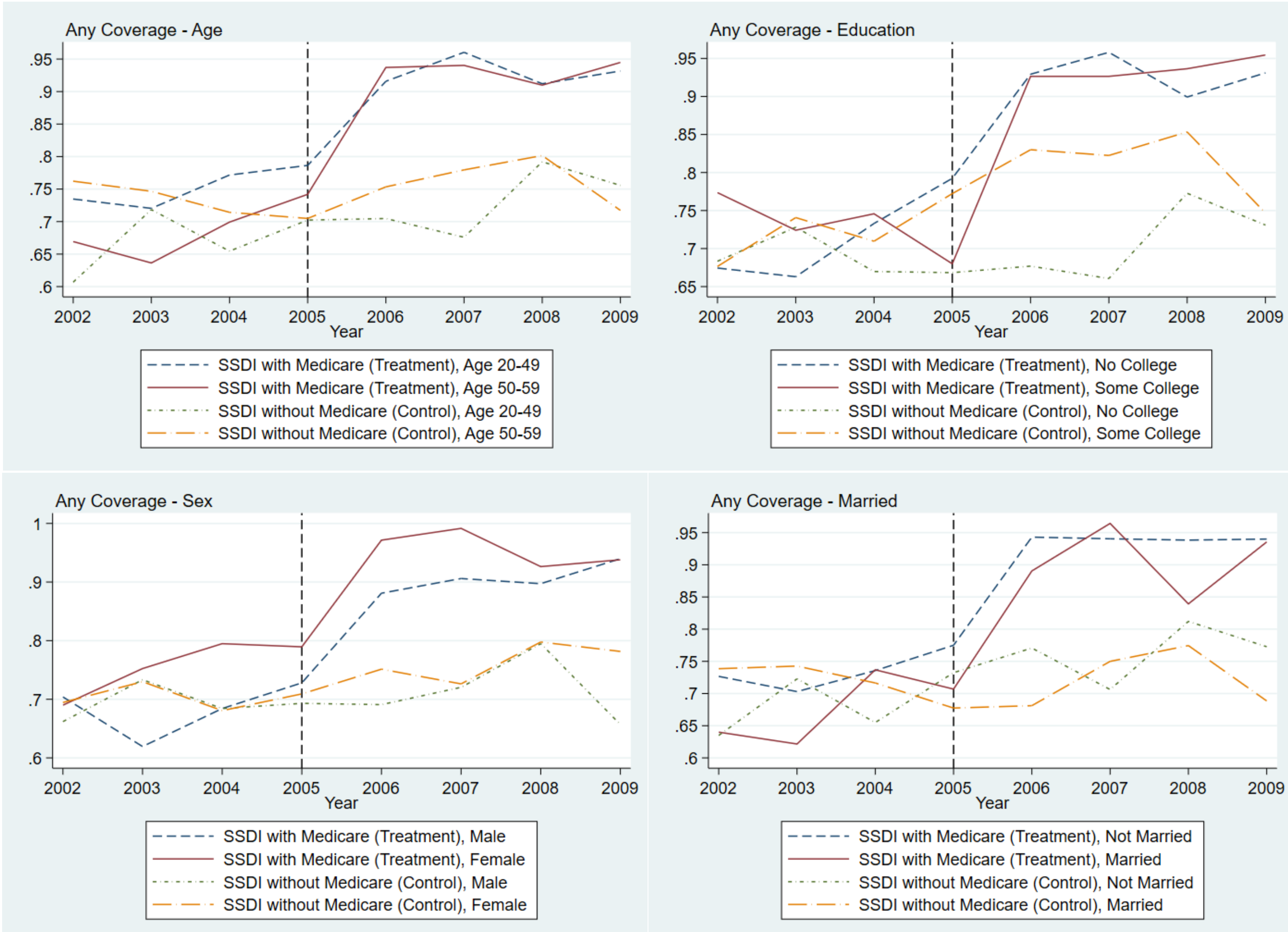
I developed trend graphs for some main outcome variables. Figure 12 shows graphs for having any prescription drug coverage. Figure 13 shows graphs for out-of-pocket (OOP) drug expenditure. Both figures show separate graphs for the heterogeneity categories: age, education, sex, and marital status. In Figure 12, most of the graphs show a large increase in coverage starting in 2006 for the treatment group. For the control group subsamples, most of the graphs show fairly flat levels of coverage. The exception is the education graph where the some college control group saw an initial gain, which decreased back to pre-period levels in 2009.

In Figure 13, the treatment group subsamples all show a decrease in post-period OOP drug expenditure. Some also show a slight decrease in the pre-period, such as individuals ages 50-59. For the control group subsamples, most of the graphs show fairly flat levels of OOP drug expenditure. The age-based graph shows a very slight decrease in post-period OOP drug expenditure for control group individuals ages 50-59.

3.4.3 Heterogeneous Effects

Table 24 shows ordinary least squares (OLS) estimates for the prescription drug outcomes of interest and heterogeneity categories. Columns (1)-(2) show estimates for the age subsamples. Based on the coefficient estimates, individuals ages 50-59 experienced higher levels of coverage gains (22.5 percentage points [33 percent] versus 13.1 percentage points [17 percent]) and larger decreases in OOP drug expenditure (decrease of $712 [44 percent] versus decrease of $242 [29 percent]). The total drug expenditure coefficients suggest larger increases

Figure 12. Any Coverage - By Heterogeneity Categories



Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease. Standard deviations in parentheses.

Figure 13. OOP Expenditure - By Heterogeneity Categories

Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease. Expenditure amounts are in 2007 dollars. Standard deviations in parentheses.

Table 24. OLS Estimates of Medicare Part D Introduction on Prescription Drug Outcomes of Interest - by Heterogeneity Categories

	Coefficient Estimates				**Pre-Period Treatment Group Means**			
Variable	Age 20-49 (1)	Age 50-59 (2)	Educ.: No College (3)	Educ.: At Least Some College (4)	Age 20-49 (5)	Age 50-59 (6)	Educ.: No College (7)	Educ.: At Least Some College (8)
Coverage								
Any coverage	0.131***	0.225***	0.202***	0.149***	0.753	0.690	0.717	0.727
	(0.0387)	(0.0374)	(0.0327)	(0.0493)	(0.432)	(0.463)	(0.451)	(0.447)
Public coverage	0.203***	0.333***	0.274***	0.284***	0.646	0.496	0.593	0.482
	(0.0401)	(0.0375)	(0.0332)	(0.0513)	(0.479)	(0.500)	(0.492)	(0.501)
Private coverage	-0.0509	-0.0548	-0.0402	-0.0825	0.148	0.259	0.168	0.327
	(0.0356)	(0.0365)	(0.0300)	(0.0538)	(0.355)	(0.438)	(0.374)	(0.470)
Utilization								
Total utilization	2.338	1.871	3.491	-2.312	35	49	41	50
	(3.655)	(3.863)	(2.956)	(5.532)	(40)	(42)	(42)	(41)
Expenditure								
Total expenditure	477.3	69.66	25.33	660.3	3,147	3,842	3,237	4,371
	(517.9)	(427.1)	(353.6)	(696.3)	(6,807)	(4,088)	(5,564)	(5,279)
Public expenditure	765.5*	820.3***	512.7*	1,408***	1,937	1,620	1,806	1,646
	(428.0)	(317.8)	(305.2)	(439.1)	(6,053)	(2,911)	(4,996)	(3,297)
Priv. ins. expenditure	-46.09	-38.69	-59.53	92.98	369	620	300	1,115
	(200.2)	(224.6)	(103.9)	(464.1)	(1,600)	(1,987)	(1,016)	(3,107)
OOP expenditure	-242.1**	-711.9***	-427.9***	-841.1***	840	1,602	1,131	1,611
	(122.8)	(173.4)	(121.5)	(235.2)	(1,603)	(2,802)	(2,271)	(2,577)
Observations	2,060	2,235	3,025	1,270	446	526	727	245

Notes: OLS estimates for prescription drug coverage, annual utilization, and annual drug expenditure (in 2007 dollars). The total utilization variable is a count of all prescribed medications purchased during a given year, and it includes initial purchases and refills. Data from the MEPS for years 2002-2009. Includes SSDI population between ages 20-59, excluding people with chronic kidney disease (CKD). Underlying models include year fixed effects, census region fixed effects, and all controls. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses. The right side of table shows pre-period treatment group means and standard deviations.
* p<0.1, ** p<0.05, *** p<0.01

Table 24. OLS Estimates of Medicare Part D Introduction on Prescription Drug Outcomes of Interest - by Heterogeneity Categories (continued)

	Coefficient Estimates				Pre-Period Treatment Group Means			
Variable	Male (9)	Female (10)	Married (11)	Not Married (12)	Male (13)	Female (14)	Married (15)	Not Married (16)
Coverage								
Any coverage	0.223***	0.153***	0.253***	0.140***	0.683	0.760	0.675	0.737
	(0.0431)	(0.0350)	(0.0471)	(0.0340)	(0.466)	(0.427)	(0.469)	(0.440)
Public coverage	0.325***	0.239***	0.439***	0.206***	0.497	0.642	0.353	0.652
	(0.0410)	(0.0365)	(0.0461)	(0.0358)	(0.500)	(0.480)	(0.479)	(0.477)
Private coverage	-0.0509	-0.0446	-0.0935*	-0.0510*	0.259	0.149	0.392	0.132
	(0.0415)	(0.0320)	(0.0499)	(0.0308)	(0.439)	(0.357)	(0.489)	(0.339)
Utilization								
Total utilization	3.760	1.592	3.144	1.056	37	49	49	40
	(3.642)	(3.721)	(4.756)	(3.230)	(39)	(44)	(45)	(40)
Expenditure								
Total expenditure	906.6**	-235.2	773.9	-13.20	2,923	4,205	3,547	3,513
	(444.8)	(473.9)	(494.8)	(438.0)	(4,178)	(6,655)	(3,982)	(6,033)
Public expenditure	1,171***	566.4	1,465***	477.6	1,286	2,310	964	2,095
	(302.9)	(396.2)	(336.8)	(352.4)	(2,889)	(5,976)	(2,307)	(5,258)
Priv. ins. expenditure	92.28	-82.63	-105.2	22.83	606	391	1,043	284
	(269.1)	(178.7)	(299.6)	(191.0)	(2,159)	(1,337)	(2,636)	(1,294)
OOP expenditure	-357.1***	-719.0***	-586.3***	-513.6***	1,031	1,504	1,539	1,134
	(124.6)	(184.8)	(177.4)	(137.4)	(1,812)	(2,838)	(2,251)	(2,394)
Observations	1,857	2,438	1,610	2,685	517	455	283	689

Notes: OLS estimates for prescription drug coverage, annual utilization, and annual drug expenditure (in 2007 dollars). The total utilization variable is a count of all prescribed medications purchased during a given year, and it includes initial purchases and refills. Data from the MEPS for years 2002-2009. Includes SSDI population between ages 20-59, excluding people with chronic kidney disease (CKD). Underlying models include year fixed effects, census region fixed effects, and all controls. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses. The right side of table shows pre-period treatment group means and standard deviations.
* p<0.1, ** p<0.05, *** p<0.01

for individuals ages 20-49 ($477 [15 percent] versus $70 [2 percent]) but neither of the coefficient estimates is statistically significant at the 10 percent level.

Turning to columns (3)-(4), the columns show estimates for the education subsamples. Based on the coefficient estimates, individuals with at least some college experienced lower levels of coverage gains (14.9 percentage points [20 percent] versus 20.2 percentage points [28 percent]), but these individuals experienced larger increases in public drug expenditure ($1,408 [86 percent] versus $513 [28 percent]) and larger decreases in OOP drug expenditure (decrease of $841 [52 percent] versus decrease of $428 [38 percent]). The total drug expenditure coefficients suggest larger increases for individuals with at least some college ($660 [15 percent] versus $25 [1 percent]), but neither of the coefficient estimates is statistically significant at the 10 percent level.

Columns (9)-(10) show estimates for subsamples by sex. Based on the coefficient estimates, men experienced larger gains in any drug coverage (22.3 percentage points [33 percent] versus 15.3 percentage points [20 percent]) and public drug coverage (32.5 percentage points [65 percent] versus 23.9 percentage points [37 percent]). The coefficient estimates suggest that men experienced larger increases in total drug expenditure (increase of $907 [31 percent] versus decrease of $235 [6 percent]) and public drug expenditure ($1,171 [91 percent] versus $566 [25 percent]), but the coefficient estimates suggest women experienced larger decreases in out-of-pocket drug expenditure (decrease of $719 [48 percent] versus decrease of $357 [35 percent]).

Columns (11)-(12) show estimates for subsamples by marital status. Based on the coefficient estimates, married individuals experienced larger increases in any drug coverage (25.3 percentage points [37 percent] versus 14.0 percentage points [19 percent]), public drug coverage (43.9 percentage points [124 percent] versus 20.6 percentage points [32 percent]), and public drug expenditure ($1,465 [152 percent] versus $478 [23 percent]). The total drug expenditure coefficients suggest larger increases for married individuals (increase of $774 [22 percent] versus decrease of $13 [0.4 percent]), but neither of the coefficient estimates is statistically significant at the 10 percent level. The out-of-pocket drug expenditure estimates are similar in size for both married individuals and unmarried individuals (decrease of $586 [38 percent] versus decrease of $514 [45 percent]).

3.4.4 Effects on Other Health Care Expenditure and Utilization

Table 25 shows OLS estimates when the outcome is other health care expenditure, other health care utilization, or prescription drug prices. The top part of the table shows estimates for expenditure outcomes. Only one outcome (hospital outpatient expenditure) has a statistically significant coefficient, and the coefficient is only statistically significant at the 10 percent level. The coefficient estimates suggest an increase in office-based visit expenditure ($366 or 22 percent), an increase in hospital outpatient expenditure ($449 or 97 percent), a slight decrease in emergency room expenditure ($4 or 2 percent), and a decrease in hospital inpatient expenditure ($343 or 11 percent).

The middle part shows estimates for the utilization amounts. None of the estimates is statistically significant at the 10 percent level. The coefficient estimates suggest a decrease in office-based visits (1.209 visits or 10 percent), an increase in hospital outpatient visits (0.460 visits or 41 percent), a decrease in emergency room visits (0.044 visits or 8 percent), an increase in inpatient hospital discharges (0.009 discharges or 3 percent), and a decrease in inpatient hospital nights (0.120 nights or 5 percent).

Table 25. OLS Estimates of Medicare Part D Introduction on Health Care Expenditure and Utilization Outcomes of Interest

Variable	Pre-2006 treatment group mean (1)	Estimate (2)
Expenditure		
Total medical	10,994.30	1,128
	(18,167.26)	(1,261)
Office-based visit	1,670.57	365.9
	(2,790.88)	(279.1)
Hospital outpatient	463.72	448.8*
	(1,573.37)	(229.4)
Emergency room	280.80	-4.427
	(1,110.70)	(71.02)
Hospital inpatient	3,241.21	-342.8
	(10,832.56)	(884.6)
Utilization		
Office-based visit	12.48	-1.209
	(16.83)	(1.087)
Hospital outpatient	1.12	0.460
	(3.19)	(0.299)
Emergency room	0.52	-0.0439
	(1.22)	(0.0687)
Hospital inp. discharges	0.34	0.00898
	(0.80)	(0.0505)
Hospital inp. nights	2.61	-0.120
	(10.64)	(0.616)
Prescription drug prices		
Prices	72.36	6.637
	(74.10)	(7.406)
Observations	972	4,295

Notes: OLS estimates for other health care expenditure, other health care utilization, and prescription drug prices (column (2)). Pre-period means and standard deviations (in parentheses) for the treatment group are in column (1). See Table 24 for notes on data, model, and estimation.
* $p<0.1$, ** $p<0.05$, *** $p<0.01$

The bottom part shows the estimated change in prescription drug prices for individuals. The coefficient estimate suggests an increase in average prices ($6.64 or 9 percent). The estimate is not statistically significant at the 10 percent level.

3.4.5 Effects on Self-Reported Health Status

Table 26 shows OLS estimates for the two variables related to perceived health status. The top part shows estimates for the perceived health status variable, and the bottom part shows estimates for the perceived mental health status variable. For perceived health status, the estimates suggest a large decrease in individuals reporting “Poor” health status (decrease of 9.05 percentage points or 29 percent). The estimates also suggest an increase in individuals reporting “Fair” health status (increase of 4.35 percentage points or 14 percent) and individuals reporting “Good” or better health status (increase of 4.70 percentage points or 12 percent). The estimate for the “Poor” health status is statistically significant at the 1 percent level, but all other estimates are not statistically significant at the 10 percent level.

The bottom part shows estimates for perceived mental health status. The estimates suggest a decrease in “Poor” mental health status (decrease of 5.11 percentage points or 37 percent). The estimates also suggest an increase in “Fair” mental health status (increase of 2.92 percentage points or 11 percent) and an increase in “Good” or better mental health status (increase of 2.19 percentage points or 4 percent). The estimate for the “Poor” mental health status is statistically significant at the 1 percent level, but all other estimates are not statistically significant at the 10 percent level.

3.4.6 Event Studies

Heterogeneity Effects. Figures D1-D16 show event study figures for the various heterogeneity categories and prescription drug outcomes. The graphs show both the coefficient

Table 26. OLS Estimates of Medicare Part D Introduction on Health Status Outcomes of Interest

Variable	Pre-2006 treatment group mean (1)	Estimate (2)
Perceived health status		
Health status	0.04	-0.00521
"Excellent"	(0.20)	(0.0169)
Health status	0.09	0.0333
"Very good"	(0.28)	(0.0219)
Health status	0.25	0.0188
"Good"	(0.44)	(0.0288)
Health status	0.31	0.0435
"Fair"	(0.46)	(0.0293)
Health status	0.31	-0.0905***
"Poor"	(0.46)	(0.0258)
Health status	0.38	0.0470
"Good" or better	(0.49)	(0.0315)
Health status	0.13	0.0281
"Very good" or better	(0.33)	(0.0257)
Perceived mental health status		
Mental health status	0.10	0.0153
"Excellent"	(0.29)	(0.0231)
Mental health status	0.14	0.0109
"Very good"	(0.35)	(0.0244)
Mental health status	0.36	-0.00434
"Good"	(0.48)	(0.0305)
Mental health status	0.26	0.0292
"Fair"	(0.44)	(0.0269)
Mental health status	0.14	-0.0511***
"Poor"	(0.35)	(0.0190)
Mental health status	0.60	0.0219
"Good" or better	(0.49)	(0.0306)
Mental health status	0.23	0.0263
"Very good" or better	(0.42)	(0.0301)
Observations	972	4,295

Notes: OLS estimates for health status outcomes of interest (column (2)). Pre-period means and standard deviations (in parentheses) for the treatment group are in column (1). See Table 24 for notes on data, model, and estimation.
* p<0.1, ** p<0.05, *** p<0.01

estimates and the corresponding 95 percent confidence intervals. Starting with Figures D1-D6, these figures show event studies for the three coverage outcomes. The post-reform point estimates suggest that the effects took hold right away for each group. Each group saw a large increase in any coverage in 2006, and the following years saw similar or slightly lower levels of coverage. The same can be said for public coverage. Regarding private coverage, most individuals experienced a decline in 2006 with similar levels or slightly lower levels of coverage in the other post-period years. The exception would be individuals with no college and married individuals, who experienced further decreases in the post-reform period.

Figures D7-D8 show figures regarding prescription drug utilization. Most post-period point estimates start positive and then move to being negative. None of the estimates, however, is statistically significant at the 5 percent level.

Figures D9-D16 show figures regarding prescription drug expenditure. For total drug expenditure in Figures D9-D10, most subgroups experienced small changes. Some exceptions are individuals ages 20-49 and individuals with some at least college education; these individuals experienced a large increase in the final year (2009), but the coefficients are not statistically significant at the 5 percent level. Men experienced a steady increase in total drug expenditure from 2007-2009, with the estimate in the final year being statistically significant at the 5 percent level.

Figures D11-D12 show public drug expenditure. Most subgroups experienced a steady increase in public drug expenditure from 2006-2009. Unmarried individuals had a large increase in 2006 followed by similar levels in the rest of the post-period years. Several, but not all, coefficient estimates are statistically significant at the 5 percent level.

Figures D13-D14 show private insurance drug expenditure. Individuals ages 20-49, individuals without any college education, and women experienced declines in private insurance drug expenditure; only a couple coefficient estimates are statistically significant at the 5 percent level. The other subgroups experienced small changes in private insurance drug expenditure.

Figures D15-D16 show out-of-pocket drug expenditure. All subgroups experienced a steady decrease in out-of-pocket drug expenditure during the post-period. Some coefficient estimates are statistically significant at the 5 percent level.

Turning to pre-period coefficient estimates, I review the estimates for all the heterogeneity effects (Figures D1-D16). Only four of the 192 pre-period coefficients are statistically significant at the 5 percent level. Three of the four coefficients are for the subgroup of individuals without any college education; the three coefficients are for three separate outcomes. Overall, the paucity of statistically significant coefficients gives me confidence that the parallel trends assumption is valid for the outcomes and subgroups; I interpret the coefficient estimates for individuals without college education more cautiously because of the three statistically significant coefficient estimates.

Looking at pre-period trends, most graphs do not display any concerning trends. The only graph that shows a pre-period trend that continues into the post-period is the out-of-pocket drug expenditure for female individuals (in Figure D16). The pre-period coefficient estimates are sloping downward, and the post-period coefficient estimates are sloping downward. The rest of the graphs do not show similar trends which gives me confidence that the parallel trends assumption is valid for the outcomes and subgroups.

Other Health Care Outcomes. Figures D17-D18 show event study figures for other health care expenditure. Most graphs show a mix of negative and positive coefficient estimates.

The office-based visit expenditure graph shows a sizable increase in 2006 that continues at that level in the post-period. None of the post-period coefficient estimates are statistically significant at the 5 percent level.

Figures D19-D20 show event study figures for other health care utilization. The graphs show a similar story as that for the other health care expenditure event studies. The exception is office-based visit utilization, which has negative coefficients in the post-period. The coefficient in 2008 is statistically significant at the 5 percent level.

Figure D21 shows an event study figure for prescription drug prices. The 2006-2007 coefficient estimates are both negative, and the years 2008-2009 show positive increasing prescription drug prices. None of the coefficient estimates, however, is statistically significant at the 5 percent level.

Turning to pre-period coefficient estimates, I review the estimates for all the other health care outcomes (Figures D17-D21). Only one of the 33 pre-period coefficient estimates is statistically significant at the 5 percent level. The lack of statistically significant estimates gives me confidence that the parallel trends assumption is valid for the outcomes. Additionally, none of the graphs shows any concerning trends in the pre-period coefficient estimates, which also gives me confidence that the parallel trends assumption is valid for the outcomes.

Perceived Health Status. Figures D22-D23 show event study figures for perceived health status. The estimates suggest a gradual decrease in individuals reporting “Poor” health status. The only statistically significant coefficient at the 5 percent level is for the year 2009. The estimates suggest small increases in “Good” or better health status for the years 2006-2007 and larger increases in the years 2008 and 2009.

Figures D24-D25 show event study figures for perceived mental health status. Similar to the perceived health status, the event study figure for "Poor" perceived mental health status shows a decrease in 2006 that held for the rest of the post-period years. None of the coefficient estimates is statistically significant at the 5 percent level. The estimates suggest small increases in "Very good" or better mental health status with a larger increase in 2008. Only the coefficient for the year 2008 is statistically significant at the 5 percent level.

Turning to pre-period coefficient estimates, I review the estimates for all the health status outcomes (Figures D22-D25). Only two of the 42 coefficients are statistically significant at the 5 percent level. The lack of statistically significant estimates gives me confidence that the parallel trends assumption is valid for the outcomes. Additionally, none of the graphs shows any concerning trends in the pre-period coefficient estimates, which also gives me confidence that the parallel trends assumption is valid for the outcomes.

3.4.7 Robustness Checks

I develop robustness checks for the other health care outcomes and the health status outcomes. The results are presented in Tables 27-29. In each table, column (1) repeats the main estimates from Tables 25-26. Tables (2)-(4) show estimates that vary the control variables used. Column (5) shows weighed least squares estimates using MEPS person weights. In Table 27, column (6) shows estimates when individuals with CKD are included; Tables 28-29 show a similar set of estimates in column (8). Columns (6)-(7) in Tables 28-29 show estimates when using a probit model or a logit model.

Table 27 shows robustness checks for the other health care expenditure and utilization outcomes. With the exception of the weighted least squares estimates (column (5)), most estimates are similar to the main estimates. For hospital outpatient expenditure, the estimates are

Table 27. Robustness Checks - Health Care Expenditure and Utilization Outcomes of Interest

Outcome	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add HH Income Controls (4)	MEPS Person Weights (5)	Include People w/ CKD (6)
Expenditure						
Total medical	**1,128**	1,265	1,159	1,102	-79.16	1,086
	(1,261)	(1,248)	(1,235)	(1,261)	(2,186)	(1,287)
Office-based visit	**365.9**	408.0	364.3	365.5	404.5	448.6
	(279.1)	(280.1)	(272.2)	(276.6)	(404.5)	(316.4)
Hospital outpatient	**448.8***	453.3**	442.4**	451.7**	489.1	299.4
	(229.4)	(222.4)	(221.6)	(228.0)	(322.7)	(270.0)
Emergency room	**-4.427**	-1.791	-0.189	-3.749	-35.68	-2.857
	(71.02)	(71.91)	(71.93)	(71.66)	(79.69)	(70.31)
Hospital inpatient	**-342.8**	-296.5	-315.5	-377.4	-472.9	-372.2
	(884.6)	(844.2)	(848.3)	(882.1)	(912.2)	(886.4)
Utilization						
Office-based visit	**-1.209**	-1.081	-1.206	-1.190	-2.347*	-0.656
	(1.087)	(1.089)	(1.076)	(1.086)	(1.351)	(1.257)
Hospital outpatient	**0.460**	0.468	0.447	0.454	0.357	-0.236
	(0.299)	(0.295)	(0.292)	(0.298)	(0.437)	(0.502)
Emergency room	**-0.0439**	-0.0619	-0.0465	-0.0433	-0.0682	-0.0367
	(0.0687)	(0.0689)	(0.0691)	(0.0687)	(0.0782)	(0.0685)
Hospital inp. discharges	**0.00898**	0.00258	0.00704	0.00868	0.00008	0.00672
	(0.0505)	(0.0499)	(0.0500)	(0.0506)	(0.0544)	(0.0518)
Hospital inp. nights	**-0.120**	-0.113	-0.0980	-0.113	0.0505	-0.120
	(0.616)	(0.623)	(0.623)	(0.619)	(0.635)	(0.594)
Prescription drug prices						
Prices	**6.637**	10.34	9.639	9.471	13.57	9.772
	(7.406)	(6.733)	(6.707)	(6.634)	(8.444)	(6.576)
Observations	**4,295**	4,295	4,295	4,295	4,084	4,357

Notes: Column (1) shows estimates from Table 25. Columns (1)-(4), (6) show OLS estimates of the coefficient of interest in equation (3.1). Column (5) shows weighted least squares estimates for the same coefficient of interest. See Table 24 for notes on data used. Column (6) uses same data set but includes people with chronic kidney disease (CKD). Underlying models include year fixed effects and census region fixed effects. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 28. Robustness Checks - Health Status Outcomes of Interest

Outcome	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add HH Income Controls (4)	MEPS Person Weights (5)	Probit Model (6)	Logit Model (7)	Include People w/ CKD (8)
Perceived health status								
Health status	**-0.00521**	-0.00961	-0.00737	-0.00617	0.0113	-0.00204	0.00353	-0.00641
"Excellent"	**(0.0169)**	(0.0172)	(0.0170)	(0.0169)	(0.0218)	(0.0182)	(0.0199)	(0.0167)
Health status	**0.0333**	0.0399*	0.0362	0.0334	0.0234	0.0325	0.0301	0.0321
"Very good"	**(0.0219)**	(0.0221)	(0.0220)	(0.0219)	(0.0293)	(0.0237)	(0.0249)	(0.0217)
Health status	**0.0188**	0.0211	0.0213	0.0188	0.0305	0.0200	0.0195	0.0200
"Good"	**(0.0288)**	(0.0289)	(0.0287)	(0.0288)	(0.0359)	(0.0289)	(0.0290)	(0.0286)
Health status	**0.0435**	0.0445	0.0417	0.0431	-0.00953	0.0367	0.0363	0.0431
"Fair"	**(0.0293)**	(0.0294)	(0.0293)	(0.0293)	(0.0354)	(0.0286)	(0.0286)	(0.0291)
Health status	**-0.0905*** **	-0.0960***	-0.0918***	-0.0891***	-0.0555*	-0.0744***	-0.0748***	-0.0887***
"Poor"	**(0.0258)**	(0.0264)	(0.0259)	(0.0259)	(0.0305)	(0.0245)	(0.0249)	(0.0258)
Health status	**0.0470**	0.0514	0.0501	0.0461	0.0651*	0.0460	0.0459	0.0456
"Good" or better	**(0.0315)**	(0.0326)	(0.0318)	(0.0315)	(0.0389)	(0.0312)	(0.0312)	(0.0313)
Health status	**0.0281**	0.0303	0.0288	0.0272	0.0346	0.0312	0.0306	0.0257
"Very good" or better	**(0.0257)**	(0.0265)	(0.0260)	(0.0257)	(0.0339)	(0.0272)	(0.0283)	(0.0255)
Observations	**4,295**	4,295	4,295	4,295	4,084	4,295	4,295	4,357
Demographics	**Y**		Y	Y	Y	Y	Y	Y
HH Income Deciles	**Y**			Y	Y	Y	Y	Y
Unemployment Rate	**Y**				Y	Y	Y	Y

Notes: Column (1) shows estimates from Table 26. Columns (1)-(4), (8) show OLS estimates of the coefficient of interest in equation (3.1). Column (5) shows weighted least squares estimates for the same coefficient of interest. Columns (6)-(7) show marginal effects estimates for the same coefficient of interest. See Table 24 for notes on data used. Column (8) uses same data set but includes people with chronic kidney disease (CKD). Underlying models include year fixed effects and census region fixed effects. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

Table 29. Robustness Checks - Mental Health Status Outcomes of Interest

Outcome	Main Estimates (1)	No Controls (2)	Add Demo. Controls (3)	Add HH Income Controls (4)	MEPS Person Weights (5)	Probit Model (6)	Logit Model (7)	Include People w/ CKD (8)
Perceived mental health status								
Mental health status	**0.0153**	0.0187	0.0170	0.0154	0.0239	0.0196	0.0223	0.0228
"Excellent"	**(0.0231)**	(0.0234)	(0.0232)	(0.0230)	(0.0305)	(0.0243)	(0.0253)	(0.0230)
Mental health status	**0.0109**	0.0168	0.0123	0.00946	0.0443	0.0111	0.0112	0.00862
"Very good"	**(0.0244)**	(0.0245)	(0.0245)	(0.0244)	(0.0319)	(0.0251)	(0.0256)	(0.0242)
Mental health status	**-0.00434**	-0.000945	-0.000517	-0.00361	-0.0197	-0.00358	-0.00404	-0.00854
"Good"	**(0.0305)**	(0.0304)	(0.0305)	(0.0305)	(0.0381)	(0.0302)	(0.0302)	(0.0302)
Mental health status	**0.0292**	0.0219	0.0244	0.0307	0.00208	0.0199	0.0217	0.0279
"Fair"	**(0.0269)**	(0.0270)	(0.0270)	(0.0269)	(0.0315)	(0.0260)	(0.0262)	(0.0267)
Mental health status	**-0.0511*****	-0.0565***	-0.0531***	-0.0519***	-0.0506**	-0.0428**	-0.0409**	-0.0507***
"Poor"	**(0.0190)**	(0.0192)	(0.0189)	(0.0190)	(0.0219)	(0.0182)	(0.0185)	(0.0187)
Mental health status	**0.0219**	0.0346	0.0287	0.0212	0.0485	0.0247	0.0212	0.0228
"Good" or better	**(0.0306)**	(0.0309)	(0.0306)	(0.0306)	(0.0365)	(0.0296)	(0.0298)	(0.0303)
Mental health status	**0.0263**	0.0355	0.0292	0.0248	0.0682*	0.0276	0.0294	0.0314
"Very good" or better	**(0.0301)**	(0.0308)	(0.0305)	(0.0301)	(0.0391)	(0.0306)	(0.0310)	(0.0300)
Observations	**4,295**	4,295	4,295	4,295	4,084	4,295	4,295	4,357

Notes: Column (1) shows estimates from Table 26. Columns (1)-(4), (8) show OLS estimates of the coefficient of interest in equation (3.1). Column (5) shows weighted least squares estimates for the same coefficient of interest. Columns (6)-(7) show marginal effects estimates for the same coefficient of interest. See Table 24 for notes on data used. Column (8) uses same data set but includes people with chronic kidney disease (CKD). Underlying models include year fixed effects and census region fixed effects. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses.
* p<0.1, ** p<0.05, *** p<0.01

similar for columns (2)-(4), but the estimates in columns (2)-(4) are statistically significant at the 5 percent level. The main estimate is statistically significant at the 10 percent level. Some estimates in column (5) are different from estimates under the other specifications. Total medical expenditure is small and negative in column (5), which is different from the main estimate. Neither estimate is statistically significant at the 10 percent level, and based on the standard errors, I cannot rule out that the estimates are similar. Office-based visit utilization is more negative in column (5); it is about twice the decrease as the main estimate. It is also statistically significant at the 10 percent level. Based on the standard errors, I cannot rule out that the estimates are similar. Hospital inpatient nights is positive in column (5), but it is negative for the main estimate. Neither of the two estimates is statistically significant at the 10 percent level. Based on the standard errors, I cannot rule out that the estimates are similar. Based on the comments above, none of the estimates change the interpretation of the main results.

Table 28 shows robustness results for the perceived health status outcomes of interest. Columns (2)-(4) show estimates that are similar to the estimates in column (1), so the estimates seem robust to changes in control variables. Column (5) shows weighted least squares estimates using MEPS person weights. Most estimates are similar to the main estimates. The exceptions are "Excellent" health status, "Fair" health status, and "Poor" health status. The "Excellent" health status estimate is positive whereas the main estimate is negative, but based on the standard errors, I cannot rule out that the estimates are similar. The "Fair" health status estimate is negative whereas the main estimate is positive; however, based on the standard errors, I cannot rule out that the estimates are similar. The "Poor" health status estimate is smaller than the main estimate and also statistically significant at the 10 percent level. Based on the standard errors, I cannot rule out that the estimates are similar. For the "Good" or better health status, the estimates are similar, but the estimate for column (5) is statistically significant at the 10 percent level. Lastly, columns (6)-(8) show similar estimates to the main estimates.

Table 29 shows robustness results for the mental health status outcomes of interest. Columns (2)-(4) show estimates that are similar to the estimates in column (1), so the estimates seem robust to changes in control variables. Column (5) has some estimates that are somewhat different than the main estimates, including the "Very good" mental health status, the "Good" or better mental health status, and the "Very good" or better mental health status. For these three outcomes, all weighed least squares estimates are larger than the main estimates; also, the "Very good" or better mental health status estimate is statistically significant at the 10 percent level. Column (6)-(8) show similar estimates to the main estimates.

3.5 Discussion

In this study, I present new evidence about the effects of Medicare Part on various outcomes of SSDI Medicare beneficiaries. I find that the policy increased coverage more for older individuals (22.5 percentage points versus 13.1 percentage points), individuals without any college education (20.2 percentage points versus 14.9 percentage points), men (22.3 percentage points versus 15.3 percentage points), and married individuals (25.3 percentage points versus 14.0 percentage points). Additionally, the policy decreased both "Poor" perceived health status (9.05 percentage points) and "Poor" perceived mental health status (5.11 percentage points). I also study the effects of the policy on other health care outcomes, but the estimates are insufficient to draw any inference.

The larger increase in coverage estimated for older individuals could be somewhat driven by the lower coverage rates before the reform (69.0 percent versus 75.3 percent). This group also saw a much larger decrease in out-of-pocket drug spending ($712 versus $242) with similarly small changes in private insurance coverage and expenditure; this would suggest a larger welfare gain for the older individuals. The larger increase for men seems driven by a lower level of coverage before the reform (68.3 percent versus 76.0 percent). Men also experienced a large increase in prescription drug expenditure as a result of the reform (increase of $907 versus decrease of $235), with the estimate statistically significant at the 5 percent level. Lastly, that married individuals saw larger coverage gains seems also driven by a lower level of coverage before the reform (67.5 percent versus 73.7 percent); married individuals also had a much larger gain in public coverage (43.9 percentage points versus 20.6 percentage points).

For the other health care outcomes, it is difficult to draw any inference. Only one estimate is statistically significant at the 10 percent level, while the rest are not statistically significant at the 10 percent level. More work is needed to draw inference regarding these outcomes; that might involve another study using a data set with a larger sample size.

Based on the estimates, I find that the policy improved health status outcomes. The estimates suggest a large decrease in individuals reporting “Poor” health status (decrease of 9.05 percentage points) and “Poor” mental health status (decrease of 5.11 percentage points). Given this is the lowest ranked health status for both health status variables, this implies that individuals reported better health status after the policy change. This is important to infer because none of the other coefficient estimates is statistically significant at the 10 percent level. Though, most of the other coefficient estimates show increases, with the exception of “Excellent” health status and “Good” mental health status; the coefficients for both of these outcomes are negative but very small (decrease of 0.00521 percentage points and 0.00434 percentage points, respectively). The coefficients suggest an increase of 4.70 percentage points for health status of “Good” or better, which fits in with the argument above. Additionally, the coefficients suggest an increase of 2.63 percentage points for mental health status of “Very good” or better.

This study highlights the importance of studying the heterogeneous effects of Medicare Part D across the SSDI Medicare population. This study also highlights the additional effects of the policy on health outcomes. The study provides some suggestive evidence that Medicare Part D improved the health of SSDI Medicare beneficiaries. More work could be done to study how this policy affected health outcomes for SSDI Medicare beneficiaries, particularly looking at health status outcomes that are not self-reported. Such a study would require more detailed data about health status outcomes that also has a larger sample.

Appendix A. Appendix Tables and Figures for Chapter 1

Table A1. Summary Statistics - Pre-Period Sample Means of Control Variables by Medicaid Expansion Status and 2012/2013 Uninsured Rate

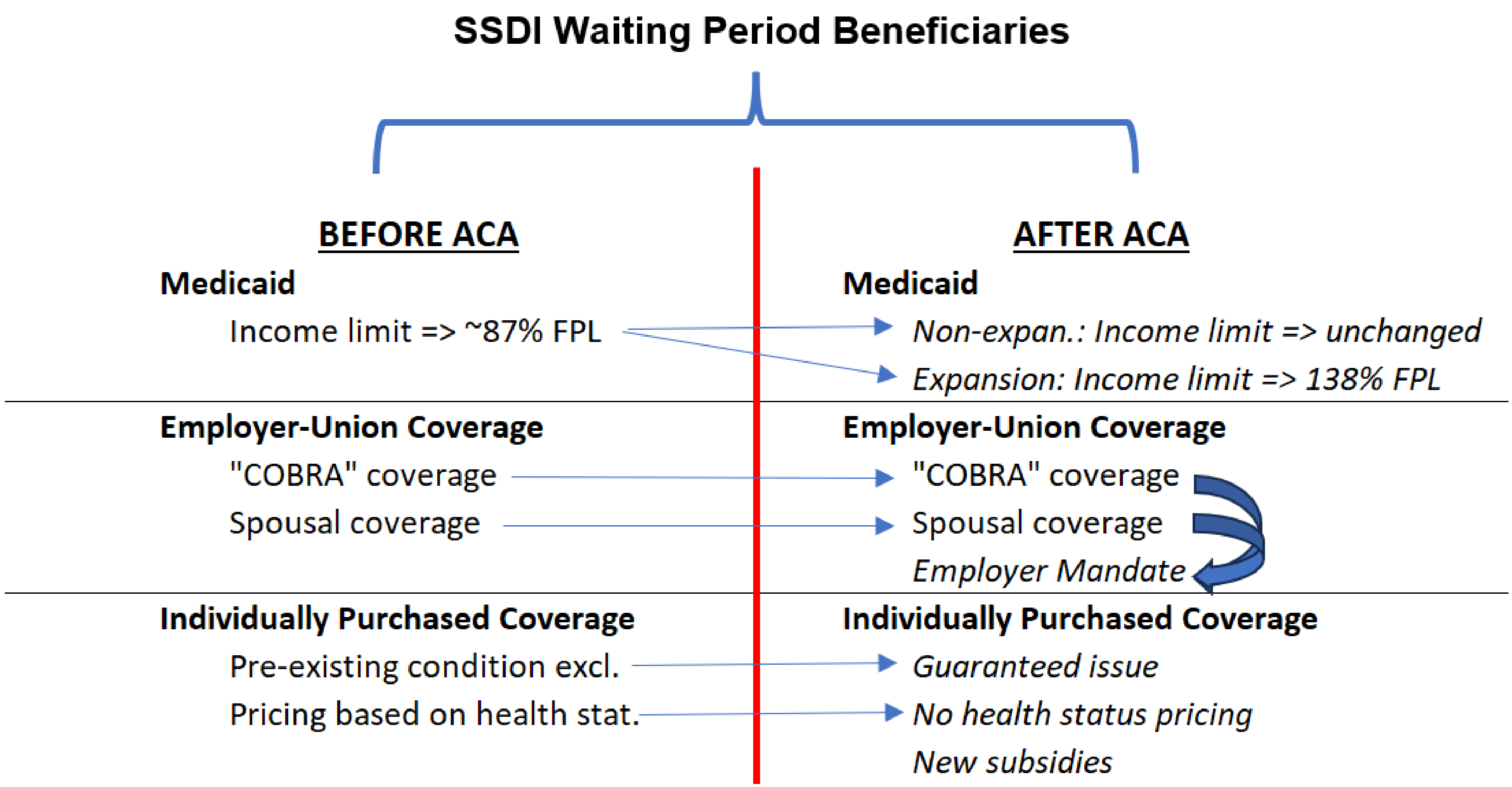
Variable	Full sample (1)	Medicaid expansion; at or above median baseline uninsured (2)	Medicaid expansion; below median baseline uninsured (3)	Non-expansion; at or above median baseline uninsured (4)	Non-expansion; below median baseline uninsured (5)
Ages 20-24	0.052	0.052	0.052	0.055	0.046
	(0.223)	(0.221)	(0.221)	(0.229)	(0.209)
Ages 25-29	0.068	0.068	0.069	0.068	0.066
	(0.252)	(0.252)	(0.254)	(0.252)	(0.247)
Ages 30-34	0.078	0.079	0.077	0.080	0.076
	(0.269)	(0.269)	(0.266)	(0.272)	(0.265)
Ages 35-39	0.093	0.098	0.087	0.097	0.098
	(0.291)	(0.297)	(0.283)	(0.295)	(0.297)
Ages 40-44	0.113	0.112	0.109	0.116	0.117
	(0.316)	(0.316)	(0.312)	(0.320)	(0.322)
Ages 45-49	0.145	0.147	0.151	0.137	0.141
	(0.352)	(0.354)	(0.358)	(0.344)	(0.348)
Ages 50-54	0.191	0.191	0.194	0.185	0.201
	(0.393)	(0.393)	(0.396)	(0.388)	(0.401)
Ages 55-59	0.259	0.254	0.261	0.262	0.255
	(0.438)	(0.435)	(0.439)	(0.440)	(0.436)
No GED/HS diploma	0.232	0.227	0.217	0.248	0.239
	(0.422)	(0.419)	(0.413)	(0.432)	(0.426)
GED/HS diploma, no college	0.367	0.390	0.350	0.370	0.382
	(0.482)	(0.488)	(0.477)	(0.483)	(0.486)
GED/HS diploma, some college	0.289	0.287	0.302	0.274	0.289
	(0.453)	(0.452)	(0.459)	(0.446)	(0.453)
Bachelors degree or higher	0.113	0.096	0.130	0.108	0.090
	(0.316)	(0.295)	(0.337)	(0.310)	(0.287)
Race/ethn. is White, Non-Hisp.	0.589	0.723	0.549	0.525	0.707
	(0.492)	(0.448)	(0.498)	(0.499)	(0.455)
Race/ethn. is Black, Non-Hisp.	0.206	0.116	0.191	0.272	0.223
	(0.404)	(0.320)	(0.393)	(0.445)	(0.417)
Race/ethn. is Hispanic	0.144	0.101	0.178	0.159	0.034
	(0.351)	(0.302)	(0.382)	(0.366)	(0.181)
Race/ethn. is all other	0.061	0.060	0.082	0.044	0.036
	(0.239)	(0.238)	(0.274)	(0.206)	(0.186)

Table A1. Summary Statistics - Pre-Period Sample Means of Control Variables by Medicaid Expansion Status and 2012/2013 Uninsured Rate (continued)

Variable	Full sample (1)	Medicaid expansion; at or above median baseline uninsured (2)	Medicaid expansion; below median baseline uninsured (3)	Non-expansion; at or above median baseline uninsured (4)	Non-expansion; below median baseline uninsured (5)
Female	0.530	0.521	0.522	0.541	0.541
	(0.499)	(0.500)	(0.500)	(0.498)	(0.498)
Married	0.356	0.355	0.351	0.359	0.372
	(0.479)	(0.479)	(0.477)	(0.480)	(0.483)
Separated	0.047	0.044	0.042	0.055	0.048
	(0.212)	(0.205)	(0.201)	(0.228)	(0.213)
Divorced	0.179	0.203	0.158	0.182	0.198
	(0.383)	(0.402)	(0.365)	(0.386)	(0.398)
Widowed	0.080	0.079	0.074	0.088	0.076
	(0.271)	(0.269)	(0.261)	(0.283)	(0.265)
Never married/single	0.338	0.320	0.374	0.316	0.307
	(0.473)	(0.466)	(0.484)	(0.465)	(0.461)
0 children	0.598	0.617	0.588	0.594	0.612
	(0.490)	(0.486)	(0.492)	(0.491)	(0.487)
1 child	0.188	0.184	0.187	0.194	0.180
	(0.391)	(0.387)	(0.390)	(0.395)	(0.384)
2 children	0.127	0.117	0.135	0.123	0.128
	(0.333)	(0.321)	(0.342)	(0.329)	(0.334)
3 children	0.057	0.055	0.060	0.056	0.048
	(0.231)	(0.228)	(0.238)	(0.230)	(0.214)
4 children	0.021	0.018	0.020	0.022	0.020
	(0.142)	(0.134)	(0.142)	(0.148)	(0.140)
5+ children	0.010	0.009	0.010	0.010	0.012
	(0.099)	(0.096)	(0.097)	(0.099)	(0.111)
State unempl. rate (%)	8.235	8.056	8.708	8.029	7.344
	(1.579)	(1.240)	(1.717)	(1.434)	(1.537)
Observations	57,681	11,440	22,094	19,151	4,996

Notes: Data from the IPUMS-ACS for years 2011-2013. Includes SSDI population between ages 20-59 without Medicare coverage. Sampling weights are used. States that expanded Medicaid between 2015-2019 are excluded. Standard deviations in parentheses.

Figure A1. Insurance Options Summary



Appendix B. Appendix Tables and Figures for Chapter 2

Table B1. OLS Estimates of Medicare Part D Introduction on Other Outcomes

	Prescription Drug Coverage		
Dependent Variable:	Public & Private Coverage	Only Public Coverage	Only Private Coverage
Parameter	(1)	(2)	(3)
$Treat_{it} \times Post_t$	0.0399**	0.237***	-0.0967***
	(0.0160)	(0.0282)	(0.0232)
Observations	4,297	4,297	4,297
Treatment group pre-2006 DV mean	0.053	0.511	0.154

Notes: OLS estimates for prescription drug coverage. See Table 16 for notes on data, model, and estimation used.
* p<0.1, ** p<0.05, *** p<0.01

Table B2. Top Five Therapeutic Subclasses of Prescription Drugs as a Share of Total Prescription Drugs (by Grouping)

Grouping	Primary Therapeutic Subclass	Percent Share
		(1)
Treatment Group, 2005 (Before Part D)	Analgesics	10.90
	Anticonvulsants	8.78
	Antidepressants	7.77
	Antihyperlipidemic Agents	4.60
	Antidiabetic Agents	4.59
Treatment Group, 2006 (After Part D)	Analgesics	10.71
	Antidepressants	8.63
	Anticonvulsants	8.01
	Antihyperlipidemic Agents	6.21
	Antidiabetic Agents	6.07
Control Group, 2005 (Before Part D)	Analgesics	9.82
	Antidiabetic Agents	9.75
	Antidepressants	8.73
	Anticonvulsants	6.63
	Antihyperlipidemic Agents	4.64
Control Group, 2006 (After Part D)	Analgesics	10.47
	Antidiabetic Agents	8.68
	Antidepressants	6.85
	Anticonvulsants	6.29
	Antihyperlipidemic Agents	5.36

Notes: Data from the MEPS. Results are split by the four difference- in-differences groupings used for the main analysis (but using only one year from the pre-period and one year from the post-period).

Table B3. Event Study Estimates (*Base year 2005*)

Dependent Variable:	Any Coverage	Public Coverage	Private Coverage	Total Utilization	Total Expend.	Public Expend.	Priv. Ins. Expend.	OOP Expend.
Parameter	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Treat_{it} \times$	-0.0356	-0.00900	-0.0325	0.454	-170.4	-124.4	-148.7	102.6
$1(t = 2002)$	(0.0537)	(0.0515)	(0.0478)	(4.537)	(407.5)	(300.4)	(175.9)	(206.0)
$Treat_{it} \times$	-0.105*	-0.0256	-0.0833*	-4.574	101.8	266.5	-259.5	94.80
$1(t = 2003)$	(0.0539)	(0.0523)	(0.0466)	(4.653)	(654.4)	(531.3)	(224.5)	(250.6)
$Treat_{it} \times$	0.00724	0.0251	-0.0351	-1.267	-26.86	-16.95	-132.4	122.4
$1(t = 2004)$	(0.0494)	(0.0485)	(0.0431)	(4.208)	(414.9)	(281.1)	(210.4)	(216.8)
$Treat_{it} \times$	0.164***	0.265***	-0.0708	4.669	17.79	530.5*	-254.4	-258.3
$1(t = 2006)$	(0.0465)	(0.0462)	(0.0448)	(4.024)	(413.2)	(317.9)	(181.2)	(180.9)
$Treat_{it} \times$	0.179***	0.320***	-0.113**	3.068	59.97	680.5	-206.6	-414.0**
$1(t = 2007)$	(0.0480)	(0.0503)	(0.0502)	(4.756)	(656.7)	(509.4)	(359.6)	(177.4)
$Treat_{it} \times$	0.0790	0.232***	-0.130**	-3.761	179.6	788.9**	-175.9	-433.4**
$1(t = 2008)$	(0.0498)	(0.0512)	(0.0504)	(4.699)	(540.2)	(387.6)	(321.8)	(182.3)
$Treat_{it} \times$	0.157***	0.279***	-0.0723	-1.857	754.4	1,460***	-24.57	-681.1***
$1(t = 2009)$	(0.0480)	(0.0489)	(0.0523)	(4.718)	(591.1)	(458.2)	(300.4)	(205.1)
Observations	4,297	4,297	4,297	4,297	4,297	4,297	4,297	4,297
F-test of pre-2006 estimates	0.1221	0.7951	0.3101	0.5852	0.9523	0.8557	0.6858	0.9448

Notes: OLS estimates reported. Data from the MEPS for years 2002-2009. Base year is 2005. Includes SSDI population between ages 20-59, excluding people with chronic kidney disease. Expenditure amounts are in 2007 dollars. Underlying models include year fixed effects, census region fixed effects, and all controls. Standard errors clustered by household and Medicare eligibility (eligible for Medicare and not eligible for Medicare) are shown in parentheses. F-test of pre-2006 estimates tests whether all pre-2006 interaction estimates equal zero; entries above display p-values of the tests.
* p<0.1, ** p<0.05, *** p<0.01

Figure B1. SSDI Benefits Timeline

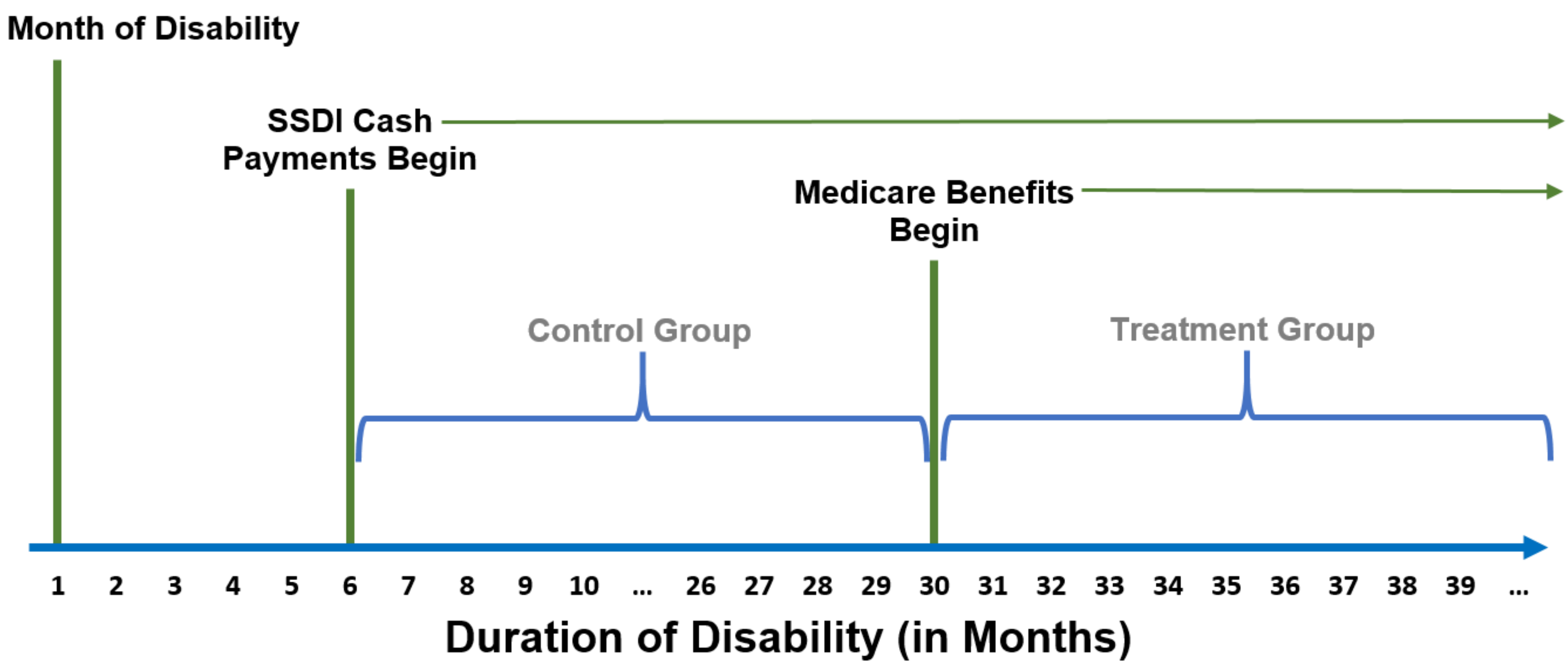
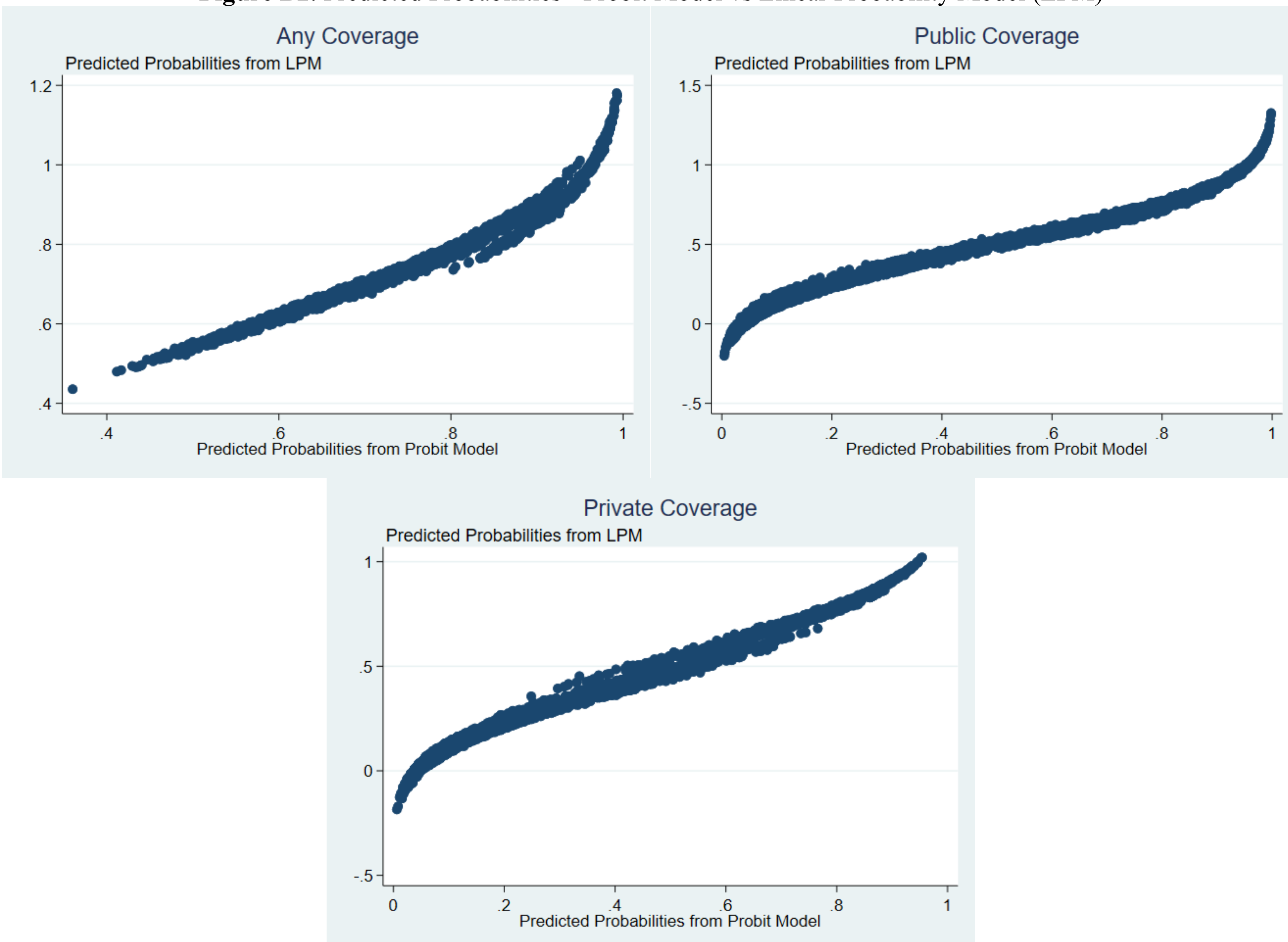
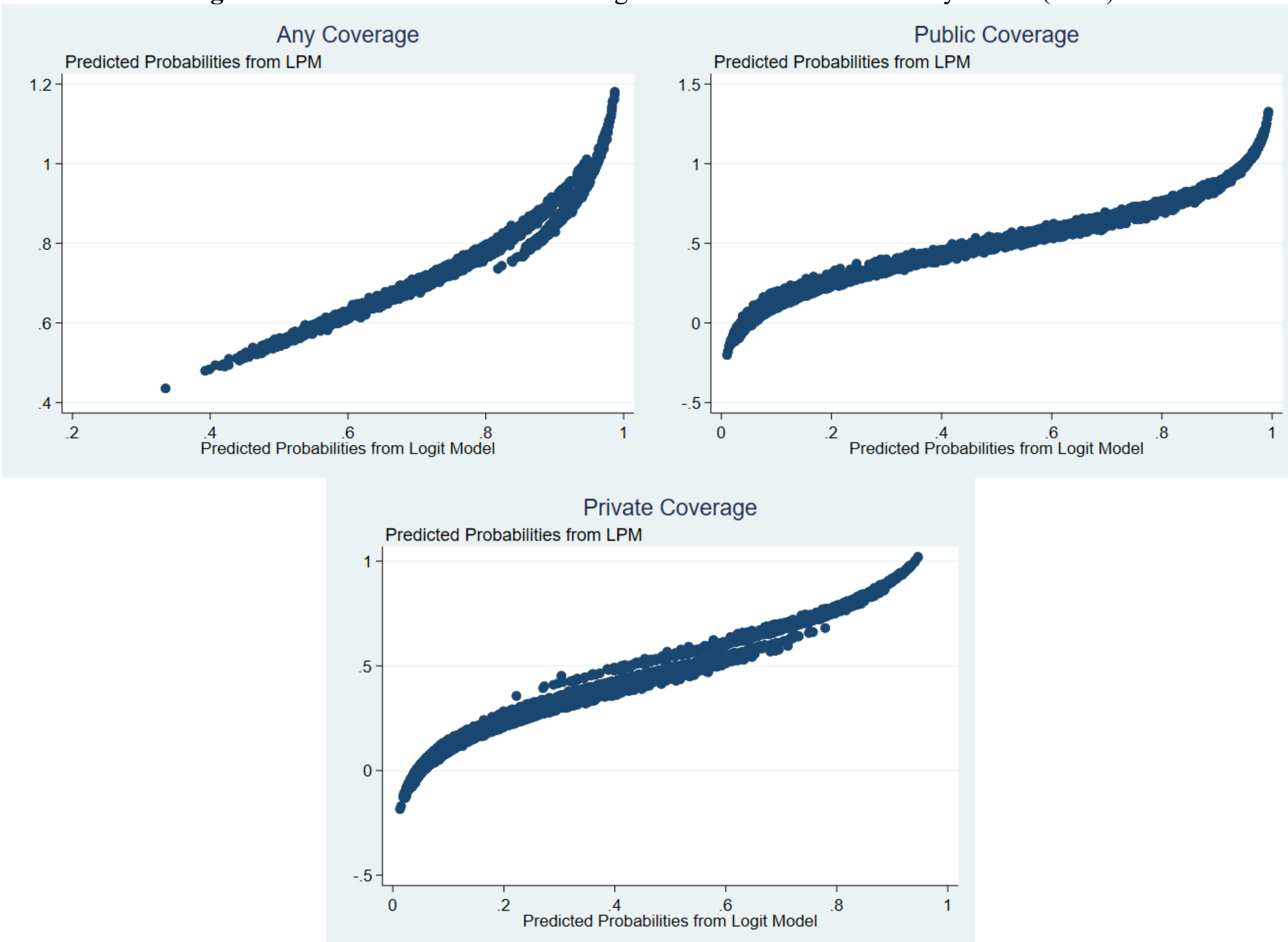


Figure B2. Predicted Probabilities - Probit Model vs Linear Probability Model (LPM)



Notes: Predicted probabilities from LPM are from regressions used for Table 16. Predicted probabilities from probit model are from the probit regressions used for Table 17.

Figure B3. Predicted Probabilities - Logit Model vs Linear Probability Model (LPM)



Notes: Predicted probabilities from LPM are from regressions used for Table 16. Predicted probabilities from logit model are from the logit regressions used for Table 17.

Figure B4. Trends in Outcomes of Interest - Prescription Drug Coverage and Annual Utilization

Notes: See Table 15 for notes on data.

Figure B5. Trends in Outcomes of Interest - Annual Prescription Drug Expenditure

Notes: See Table 15 for notes on data.

Appendix C. Replication of Engelhardt and Gruber (2011)

To build a similar data set to the one used by Engelhardt and Gruber (2011), I started by replicating some of their tables that utilize the MEPS. Below, I compare their tables to my replicated tables. For this comparison, I use the same years as they do for their analysis: 2002-2005 and 2007. Table C1 below corresponds to Table 2 from their paper. Table C2 below corresponds to Table 3 from their paper. Table C3 below corresponds to Table 4 from their paper. Table C4 below corresponds to Table 6 from their paper. Table C5 below corresponds to Table 7 from their paper.

Comparing the tables from Engelhardt and Gruber (2011) to my tables I developed using the MEPS, the results are consistent for each table. Based on our summary statistics, we both use the same number of observations. Also, the summary statistics are very close to one another. All other tables are very close to their counterpart, too.

Table C1. Comparison of Sample Means from the Original Paper (Table 2) to my Data

Variable	Engelhardt and Gruber (2011)				My Data: 2002-2005, 2007			
	Ages 60–64 before Part D (1)	Ages 60–64 after Part D (2)	Ages 65–70 before Part D (3)	Ages 65–70 after Part D (4)	Ages 60–64 before Part D (5)	Ages 60–64 after Part D (6)	Ages 65–70 before Part D (7)	Ages 65–70 after Part D (8)
Dummy if any prescription-drug coverage	0.750	0.784	0.722	0.859	0.754	0.792	0.717	0.863
Dummy if public coverage	0.080	0.076	0.260	0.657	0.079	0.076	0.259	0.658
Dummy if private coverage	0.676	0.723	0.524	0.449	0.679	0.731	0.522	0.467
Dummy if public and private coverage	0.005	0.015	0.063	0.248	0.005	0.015	0.063	0.262
Dummy if only private coverage	0.670	0.708	0.461	0.201	0.674	0.716	0.458	0.205
Dummy if only public coverage	0.074	0.061	0.198	0.409	0.074	0.061	0.196	0.396
Total prescription-drug expenditure	1,379	1,443	1,734	2,093	1,379	1,443	1,734	2,093
($2007)	(2,238)	(2,195)	(2,284)	(3,647)	(2,238)	(2,195)	(2,285)	(3,647)
Out-of-pocket prescription-drug expenditure	533	458	806	538	533	458	806	538
($2007)	(1,004)	(841)	(1,258)	(1,256)	(1,004)	(841)	(1,258)	(1,256)
Public prescription-drug expenditure	180	140	423	1,247	181	140	423	1,247
($2007)	(944)	(811)	(1,431)	(2,929)	(944)	(811)	(1,431)	(2,929)
Private plan prescription-drug expenditure	666	845	505	309	666	845	505	309
($2007)	(1,648)	(1,618)	(1,155)	(947)	(1,646)	(1,618)	(1,155)	(947)
Total medical expenditure	5,428	6,056	7,402	7,308	5,428	6,056	7,402	7,308
($2007)	(11,593)	(15,902)	(13,605)	(11,972)	(11,593)	(15,902)	(13,605)	(11,972)
Number of prescriptions	20	20	25	27	20	20	25	27
	(25)	(26)	(30)	(30)	(25)	(26)	(30)	(30)
Sample Size	4,759	1,237	5,015	1,231	4,759	1,237	5,015	1,231

Notes: Data from the MEPS. Standard deviations in parentheses.

Table C1. Comparison of Sample Means from the Original Paper (Table 2) to my Data (continued)

Variable	Engelhardt and Gruber (2011)		My Data: 2002-2005, 2007	
	Ages 65 and older before Part D	Ages 65 and older after Part D	Ages 65 and older before Part D	Ages 65 and older after Part D
	(9)	(10)	(11)	(12)
Dummy if any prescription-drug coverage	0.714	0.870	0.714	0.873
Dummy if public coverage	0.286	0.689	0.285	0.690
Dummy if private coverage	0.495	0.415	0.499	0.425
Dummy if public and private coverage	0.067	0.233	0.069	0.241
Dummy if only private coverage	0.428	0.181	0.430	0.183
Dummy if only public coverage	0.219	0.456	0.216	0.449
Total prescription-drug expenditure	1,906	2,178	1,906	2,178
($2007)	(2,794)	(3,385)	(2,794)	(3,385)
Out-of-pocket prescription-drug expenditure	948	581	948	581
($2007)	(1,436)	(1,060)	(1,437)	(1,060)
Public prescription-drug expenditure	451	1,280	451	1,280
($2007)	(1,384)	(2,691)	(1,384)	(2,691)
Private plan prescription-drug expenditure	507	318	507	318
($2007)	(1,941)	(1,062)	(1,942)	(1,062)
Total medical expenditure	8,739	9,184	8,739	9,184
($2007)	(14,983)	(15,711)	(14,893)	(15,711)
Number of prescriptions	29	31	29	31
	(30)	(31)	(30)	(31)
Sample Size	15,074	3,470	15,074	3,470

Notes: Data from the MEPS. Standard deviations in parentheses.

Table C2. Comparison of Difference-in-Difference Estimates from the Original Paper (Table 3) to my Results

Group/year	Engelhardt and Gruber (2011) Before Part D (1)	After Part D (2)	Time Difference (3)	My Results: 2002-2005, 2007 Before Part D (4)	After Part D (5)	Time Difference (6)
Panel A. Any Coverage						
Age 65-70	0.722	0.859	0.137	0.717	0.863	0.145
	(0.00798)	(0.0106)	(0.0132)	(0.00803)	(0.0105)	(0.0132)
Age 60-64	0.750	0.784	0.0342	0.754	0.792	0.0387
	(0.00795)	(0.0124)	(0.0147)	(0.00792)	(0.0122)	(0.0146)
Difference-in-difference			0.103			0.107
			(0.0198)			(0.0196)
Panel B. Public Coverage						
Age 65-70	0.260	0.657	0.397	0.259	0.658	0.399
	(0.00782)	(0.0144)	(0.0164)	(0.00782)	(0.0144)	(0.0164)
Age 60-64	0.0796	0.0760	-0.00365	0.0794	0.0760	-0.00344
	(0.00499)	(0.00781)	(0.00927)	(0.00499)	(0.00781)	(0.00927)
Difference-in-difference			0.401			0.402
			(0.0188)			(0.0188)

Notes: Each cell gives the coverage rate among 60–70 year olds for prescription-drug coverage for the different coverage sources. Standard errors clustered by household and age group (under 65 and 65 and older) are shown in parentheses.

Table C3. Comparison of the Prescription Drug Coverage Estimates from the Original Paper (Table 4) to my Results

	Engelhardt and Gruber (2011)		My Results: 2002-2005, 2007	
Explanatory variable	(1)	(2)	(3)	(4)
Panel A. 60-70 year-olds				
Reduced Form Estimates				
Dummy if 65 or older ×	0.103	0.109	0.107	0.112
Dummy if post-law change	(0.0198)	(0.0192)	(0.0196)	(0.0191)
First-stage estimates				
Dummy if 65 or older ×	0.400	0.398	0.402	0.400
Dummy if post-law change	(0.0188)	(0.0181)	(0.0188)	(0.0181)
IV estimates				
Dummy if public coverage	0.257	0.274	0.265	0.280
	(0.0467)	(0.0445)	(0.0461)	(0.0441)
Panel B. 60 and older				
Reduced Form Estimates				
Dummy if 65 or older ×	0.123	0.124	0.122	0.123
Dummy if post-law change	(0.0167)	(0.0161)	(0.0165)	(0.0160)
First-stage estimates				
Dummy if 65 or older ×	0.408	0.405	0.410	0.404
Dummy if post-law change	(0.0136)	(0.0129)	(0.0136)	(0.0130)
IV estimates				
Dummy if public coverage	0.303	0.307	0.297	0.304
	(0.0395)	(0.0372)	(0.0389)	(0.0372)
Additional Controls				
Demographics	No	Yes	No	Yes
Census division	No	Yes	No	Yes
Self-reported health status	No	Yes	No	Yes
Income quintiles	No	Yes	No	Yes

Notes: Each regression includes age and calendar year dummies. Standard errors clustered by household and age group (under 65 and 65 and older) are shown in parentheses.

Table C4. Comparison of the Prescription Drug Utilization Estimates from the Original Paper (Table 6) to my Results

Explanatory variable	Engelhardt and Gruber (2011) (1)	(2)	My Results: 2002-2005, 2007 (3)	(4)
Panel A. 60-70 year-olds				
Dummy if public coverage	3.049	3.219	3.035	3.148
	(3.392)	(3.092)	(3.377)	(3.078)
Panel B. 60 and older				
Dummy if public coverage	4.029	3.911	4.010	3.850
	(2.660)	(2.466)	(2.648)	(2.471)
Additional Controls				
Demographics	No	Yes	No	Yes
Census division	No	Yes	No	Yes
Self-reported health status	No	Yes	No	Yes
Income quintiles	No	Yes	No	Yes

Notes: Each regression includes age and calendar year dummies. Standard errors clustered by household and age group (under 65 and 65 and older) are shown in parentheses.

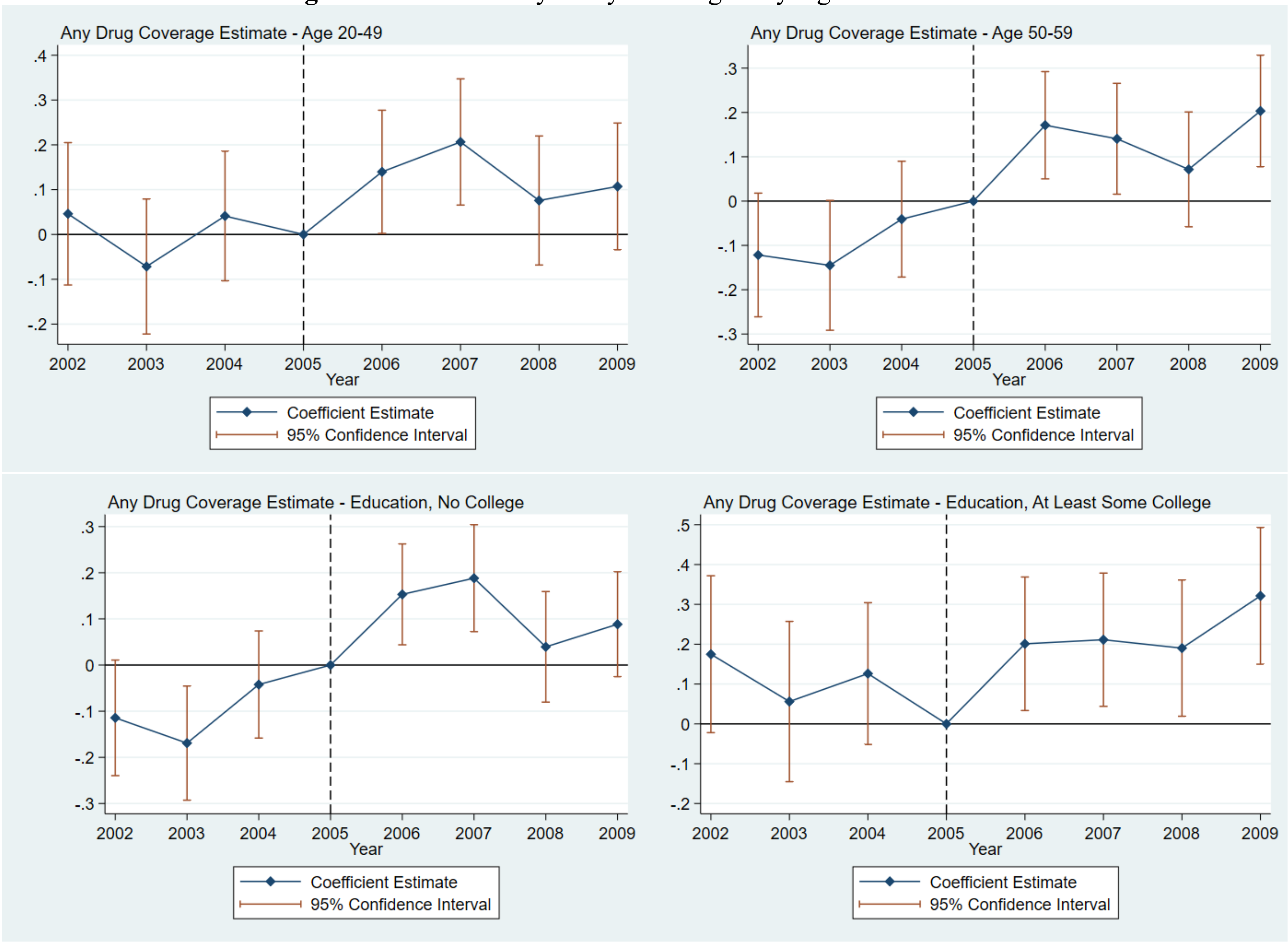
Table C5. Comparison of the Prescription Drug Expenditure Estimates from the Original Paper (Table 7) to my Results

Explanatory variable	Engelhardt and Gruber (2011)		My Results: 2002-2005, 2007	
	(1)	(2)	(3)	(4)
Panel A. Public prescription-drug expenditure				
Dummy if public coverage	2,141	2,148	2,139	2,144
	(127.2)	(127.6)	(127.1)	(128.3)
Panel B. Total prescription-drug expenditure				
Dummy if public coverage	524.3	534.8	523.8	537.6
	(240.0)	(231.7)	(239.8)	(232.9)
Public prescription-drug expenditure	0.245	0.251	0.245	0.251
	(0.104)	(0.100)	(0.104)	(0.101)
Panel C. Private group and non-group plan prescription-drug expenditure				
Dummy if public coverage	-897.8	-914.2	-896.9	-908.8
	(146.7)	(144.0)	(146.6)	(144.7)
Public prescription-drug expenditure	-0.419	-0.426	-0.419	-0.424
	(0.0732)	(0.0714)	(0.0717)	(0.0719)
Panel D. Out-of-pocket prescription-drug expenditure				
Dummy if public coverage	-718.7	-699.4	-718.0	-697.7
	(96.53)	(94.60)	(96.45)	(94.99)
Public prescription-drug expenditure	-0.336	-0.326	-0.336	-0.325
	(0.0510)	(0.0494)	(0.0510)	(0.0497)
Additional Controls				
Demographics	No	Yes	No	Yes
Census division	No	Yes	No	Yes
Self-reported health status	No	Yes	No	Yes
Income quintiles	No	Yes	No	Yes

Notes: Each regression includes age and calendar year dummies. Standard errors clustered by household and age group (under 65 and 65 and older) are shown in parentheses.

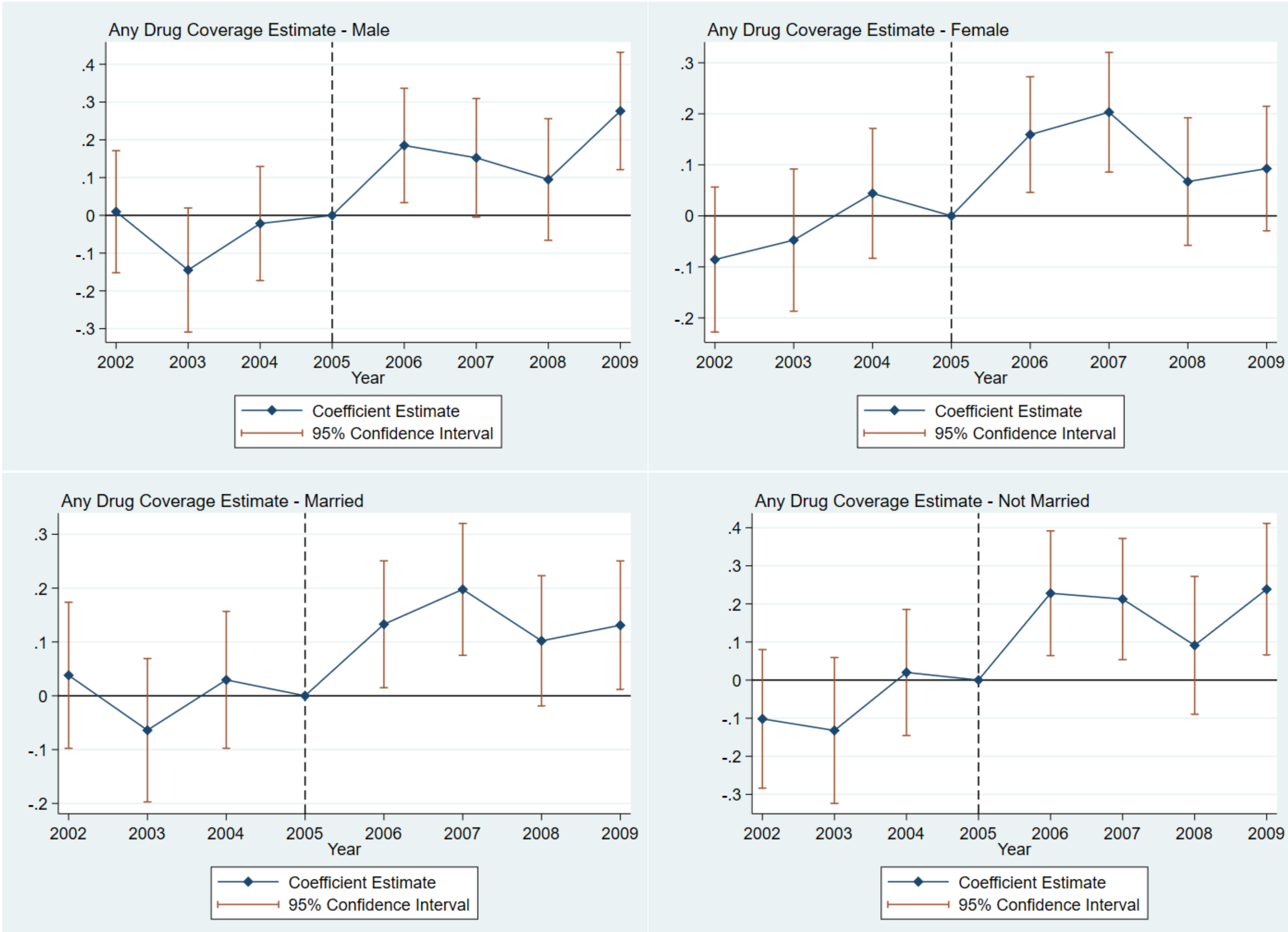
Appendix D. Appendix Tables and Figures for Chapter 3

Figure D1. Event Study - Any Coverage - By Age and Education



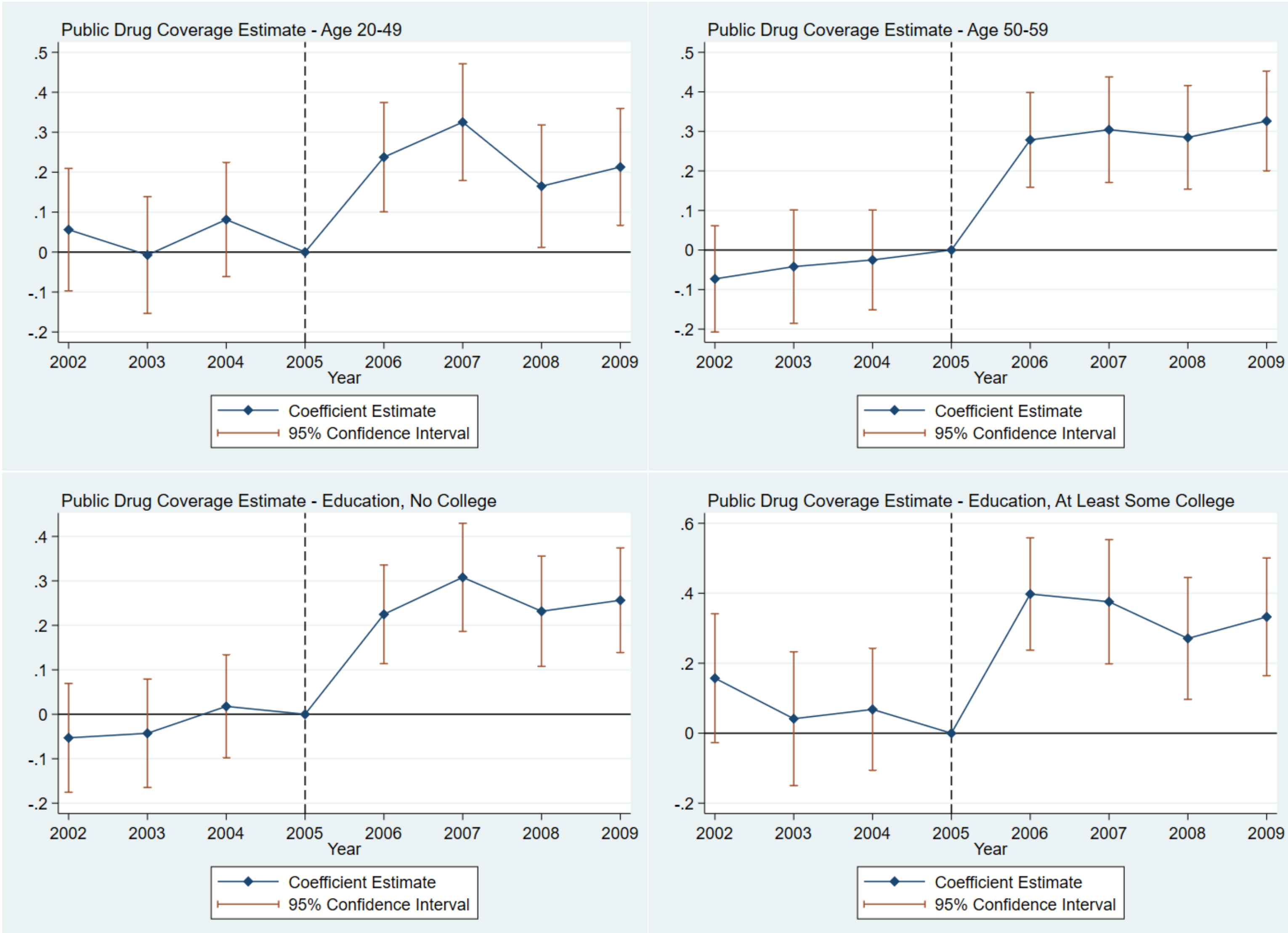
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D2. Event Study - Any Coverage - By Sex and Marital Status



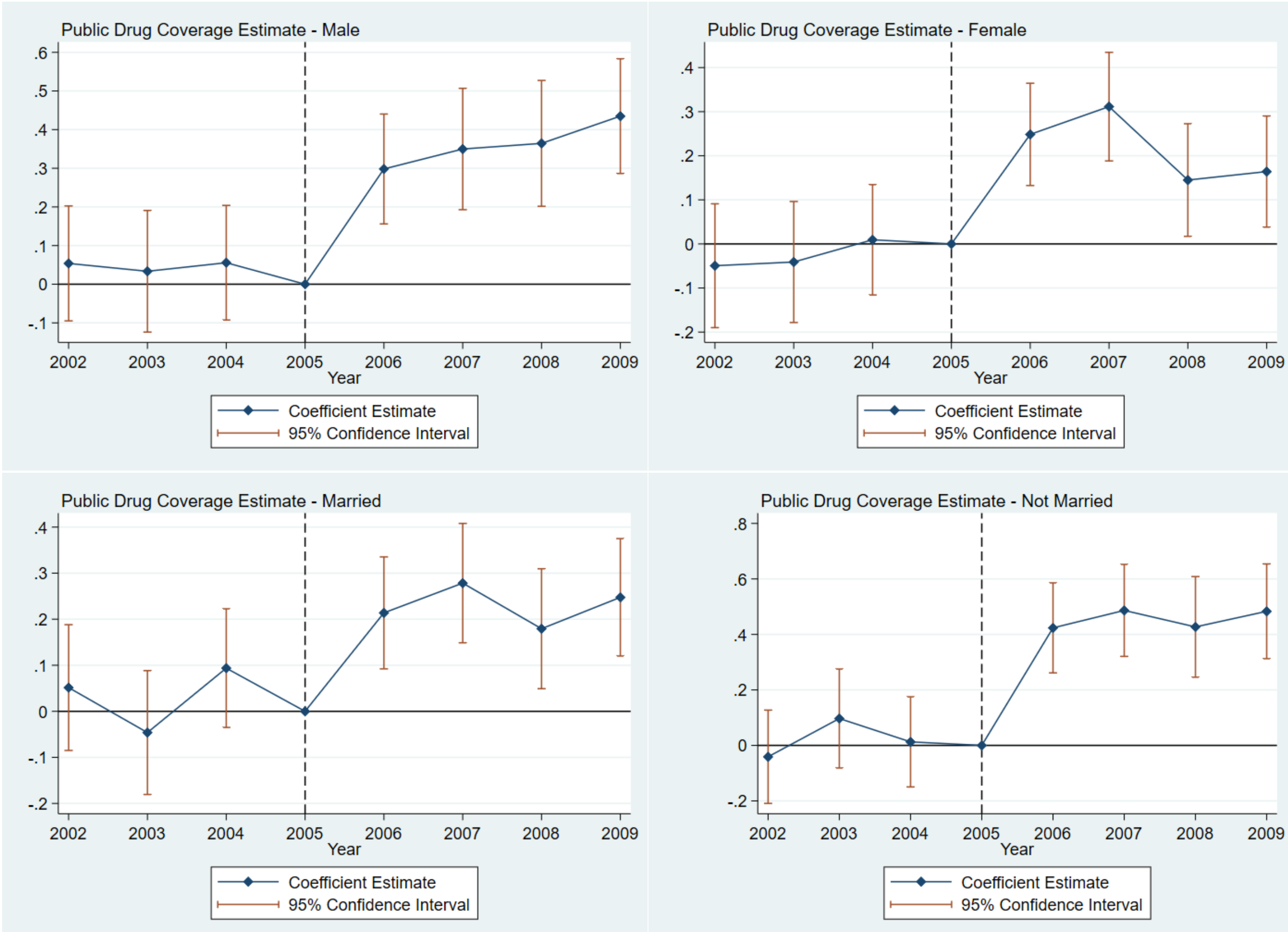
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D3. Event Study - Public Coverage - By Age and Education



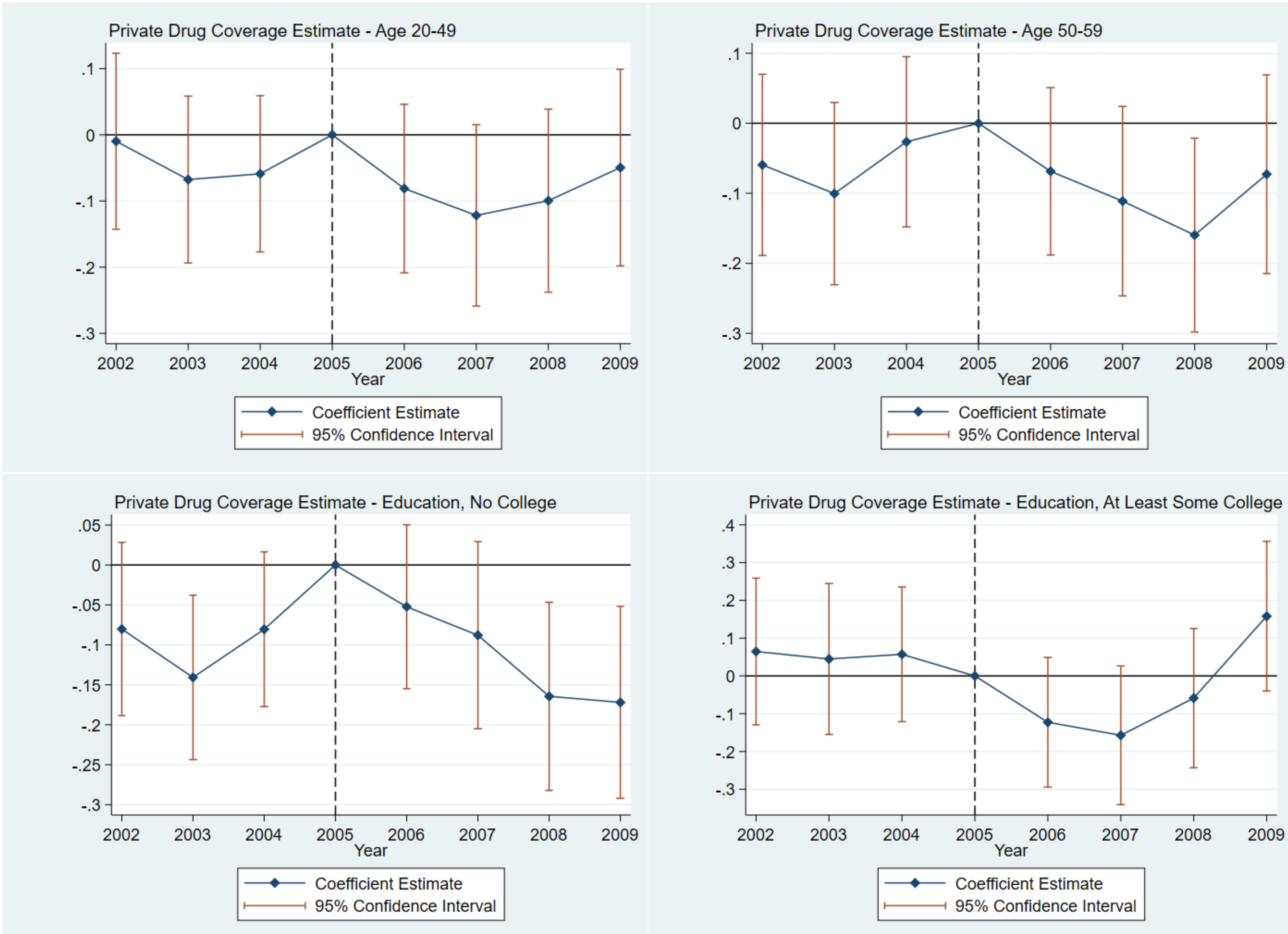
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D4. Event Study - Public Coverage - By Sex and Marital Status



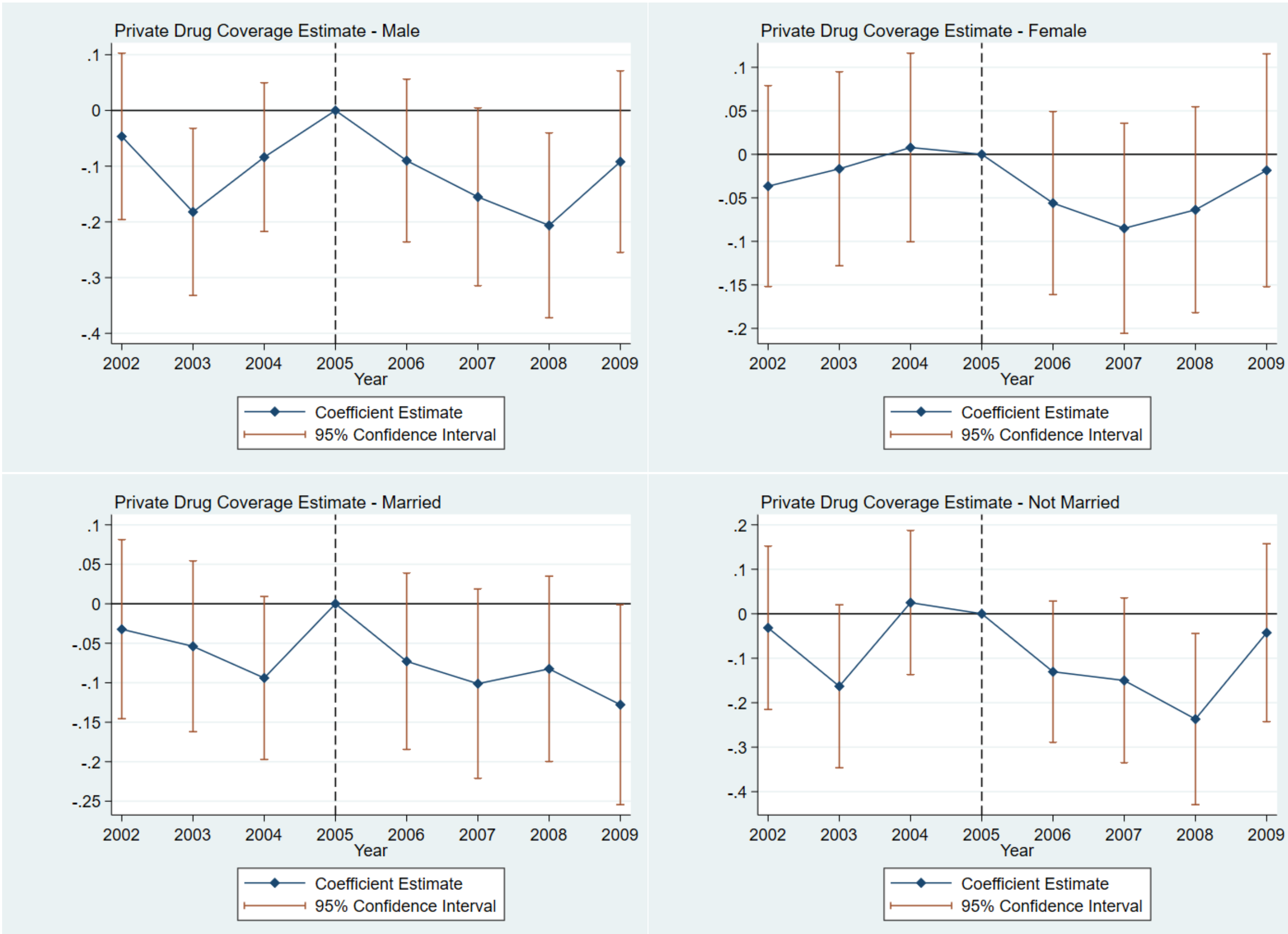
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D5. Event Study - Private Coverage - By Age and Education



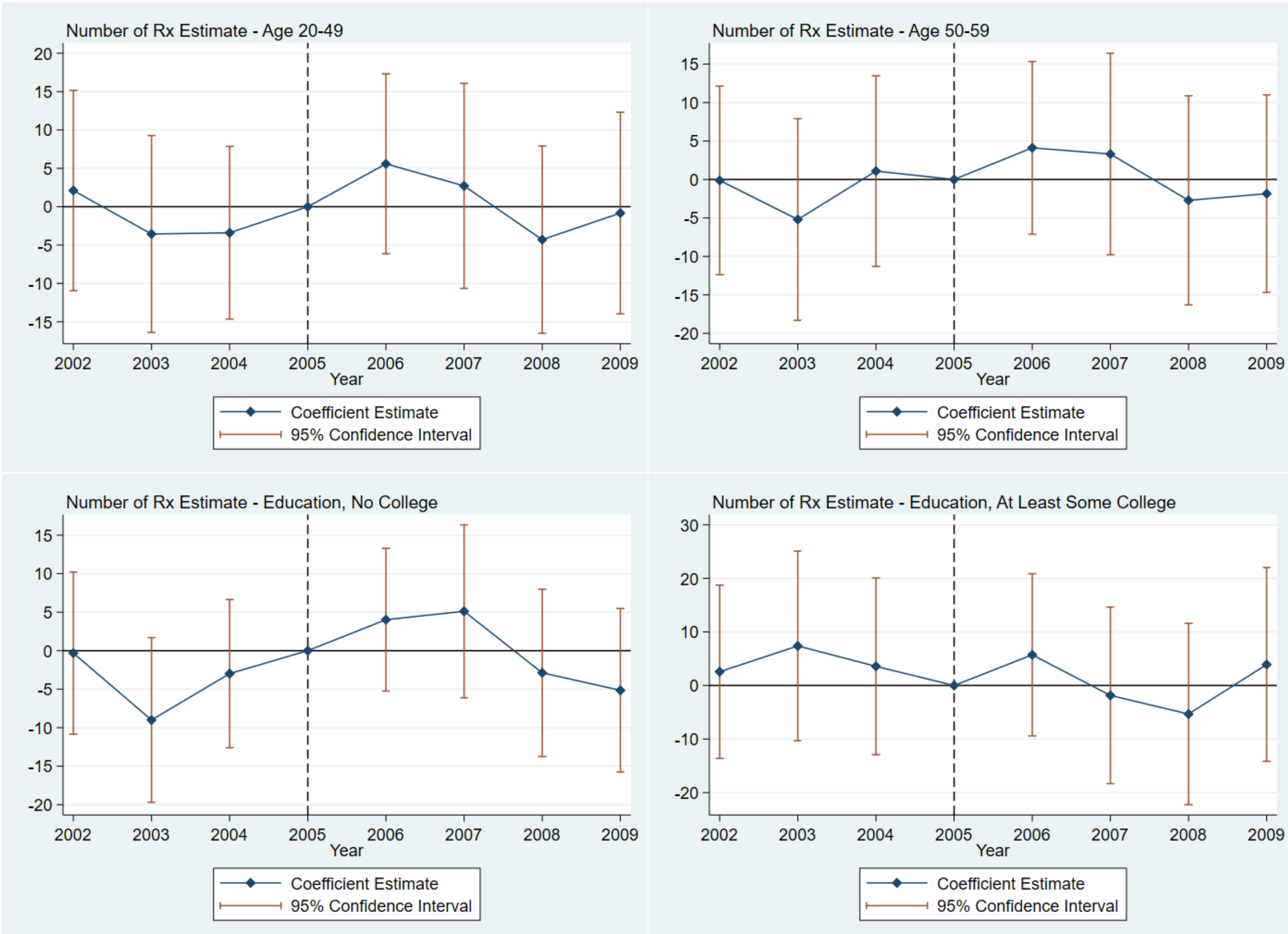
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D6. Event Study - Private Coverage - By Sex and Marital Status



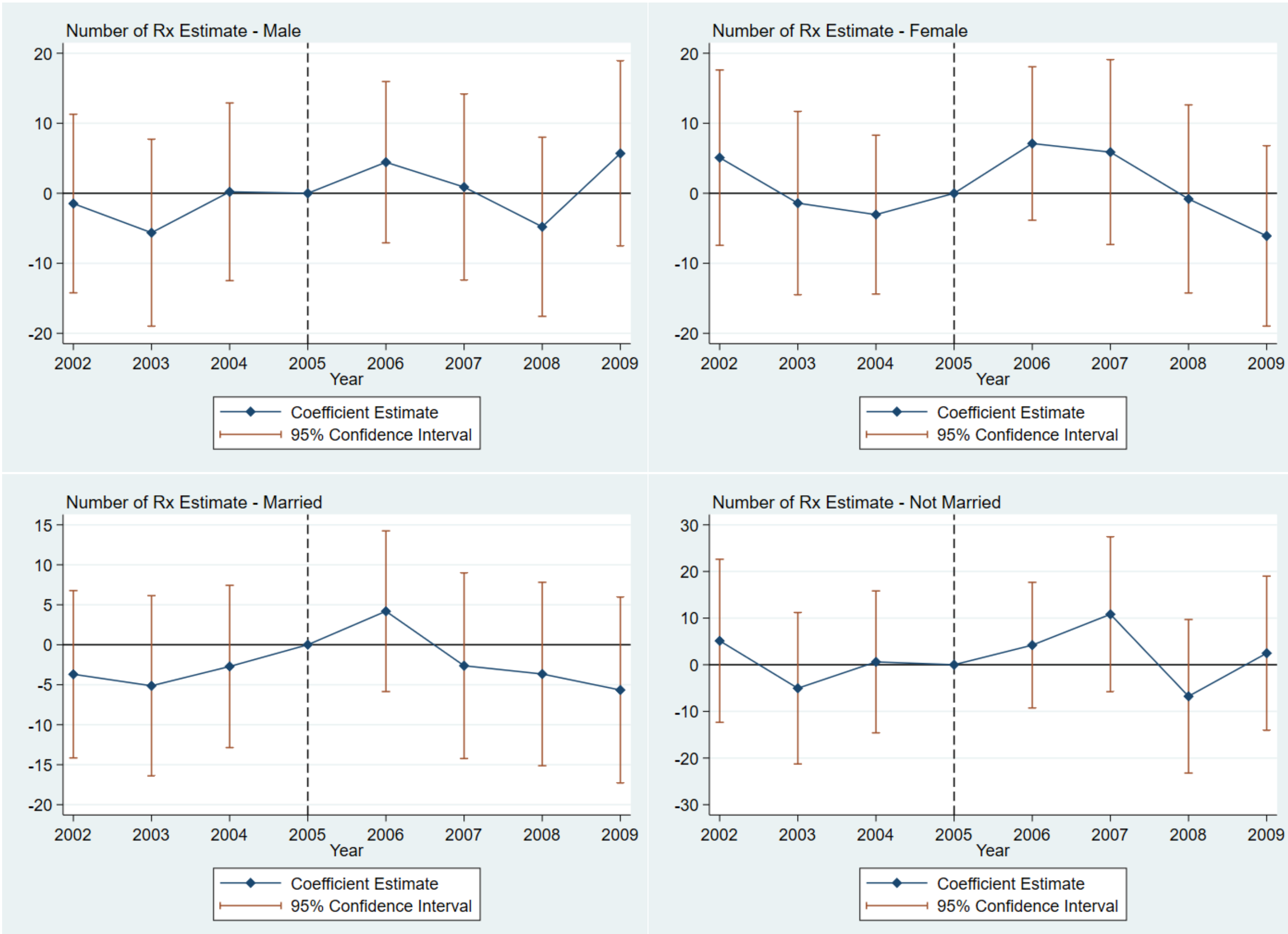
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D7. Event Study - Number of Prescriptions - By Age and Education



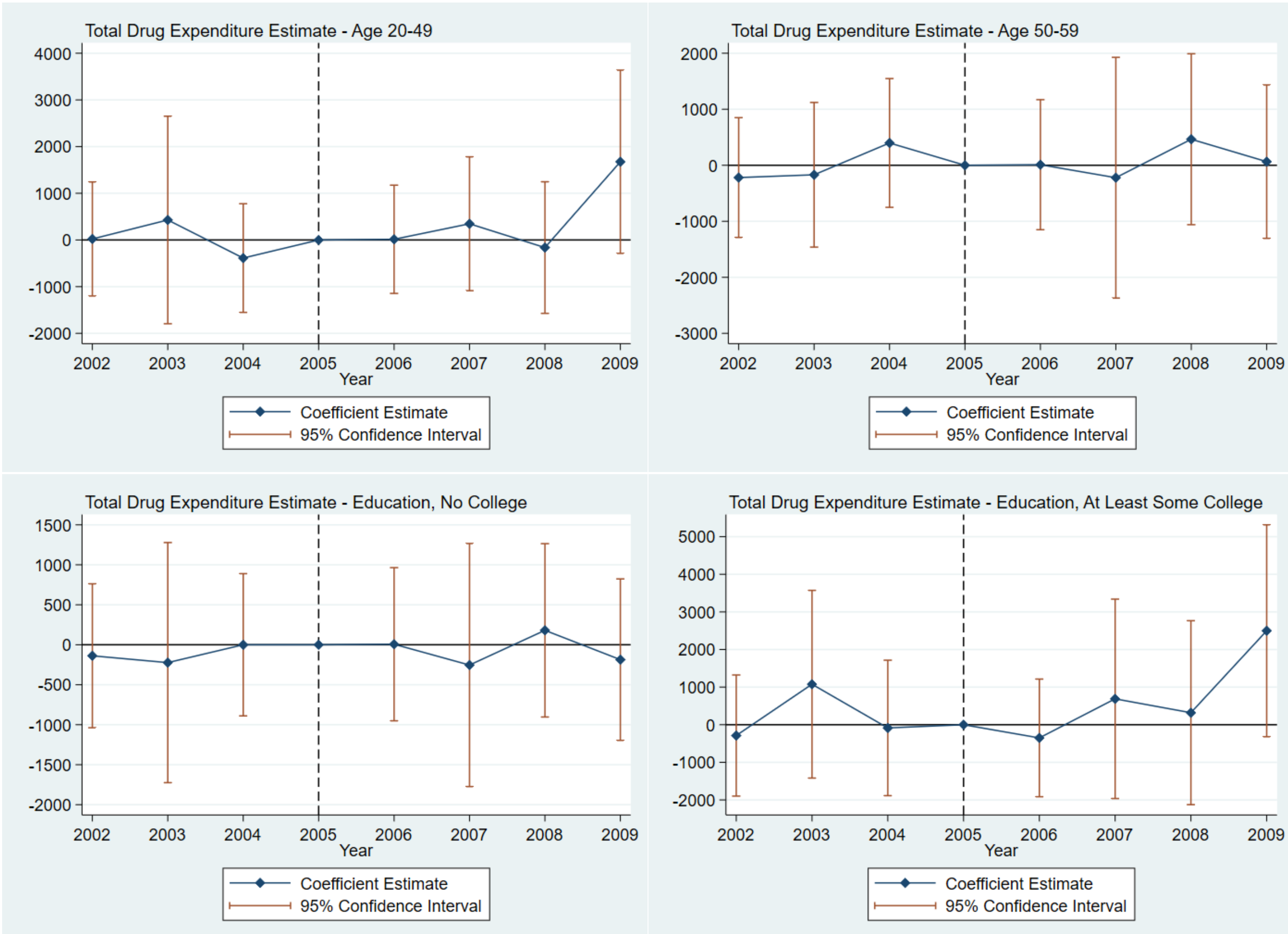
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D8. Event Study - Number of Prescriptions - By Sex and Marital Status



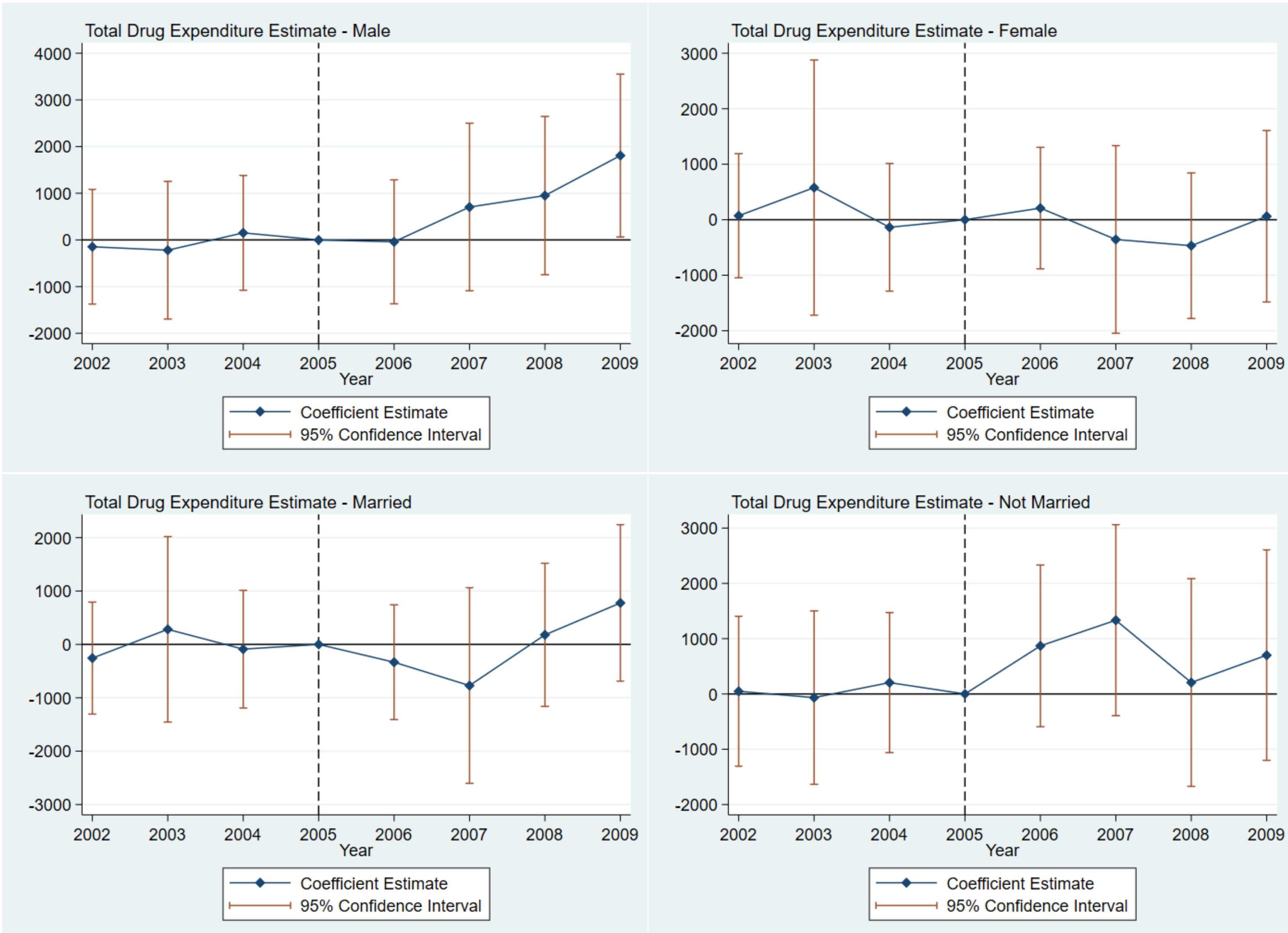
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D9. Event Study - Total Drug Expenditure - By Age and Education



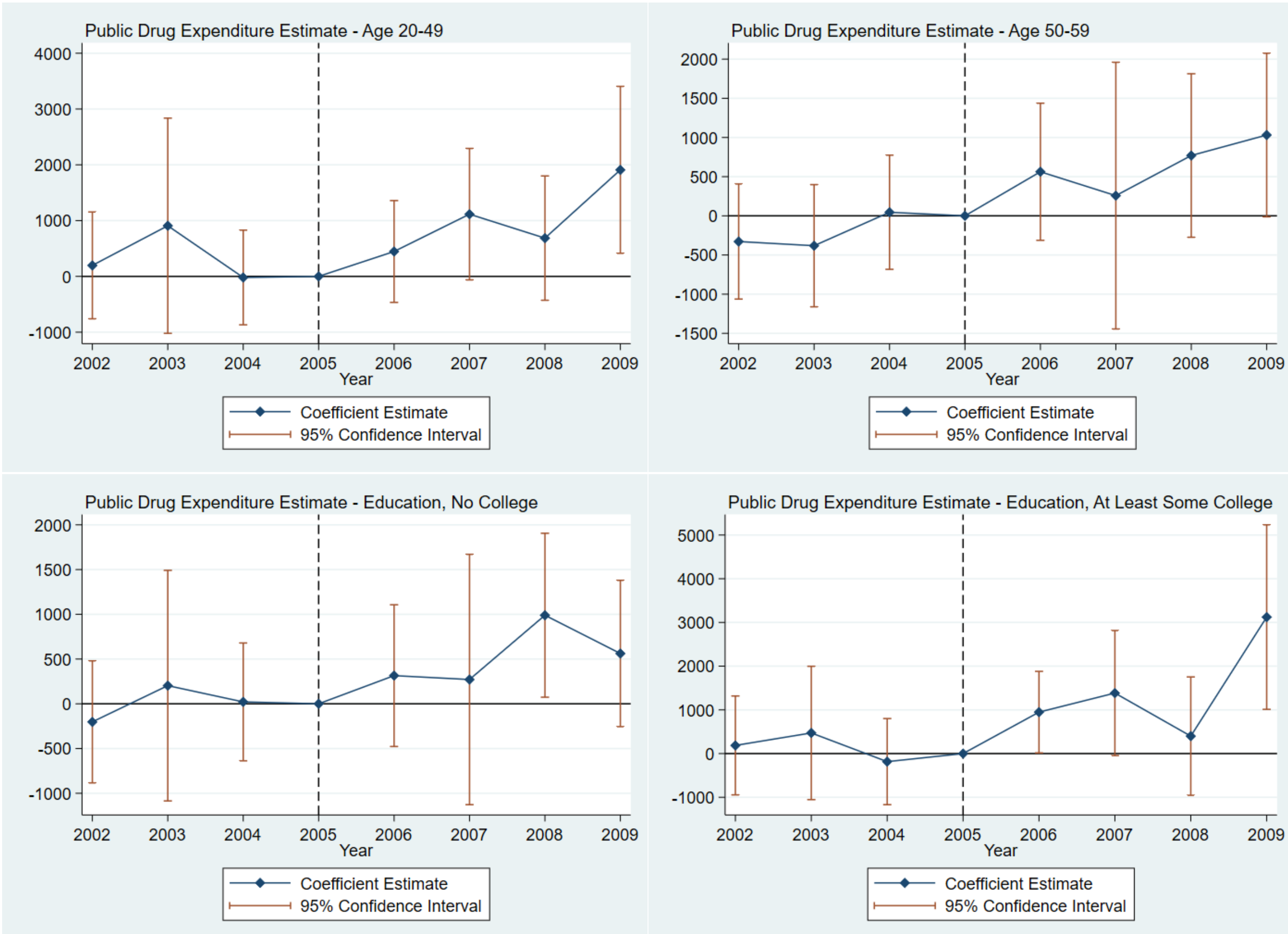
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D10. Event Study - Total Drug Expenditure - By Sex and Marital Status



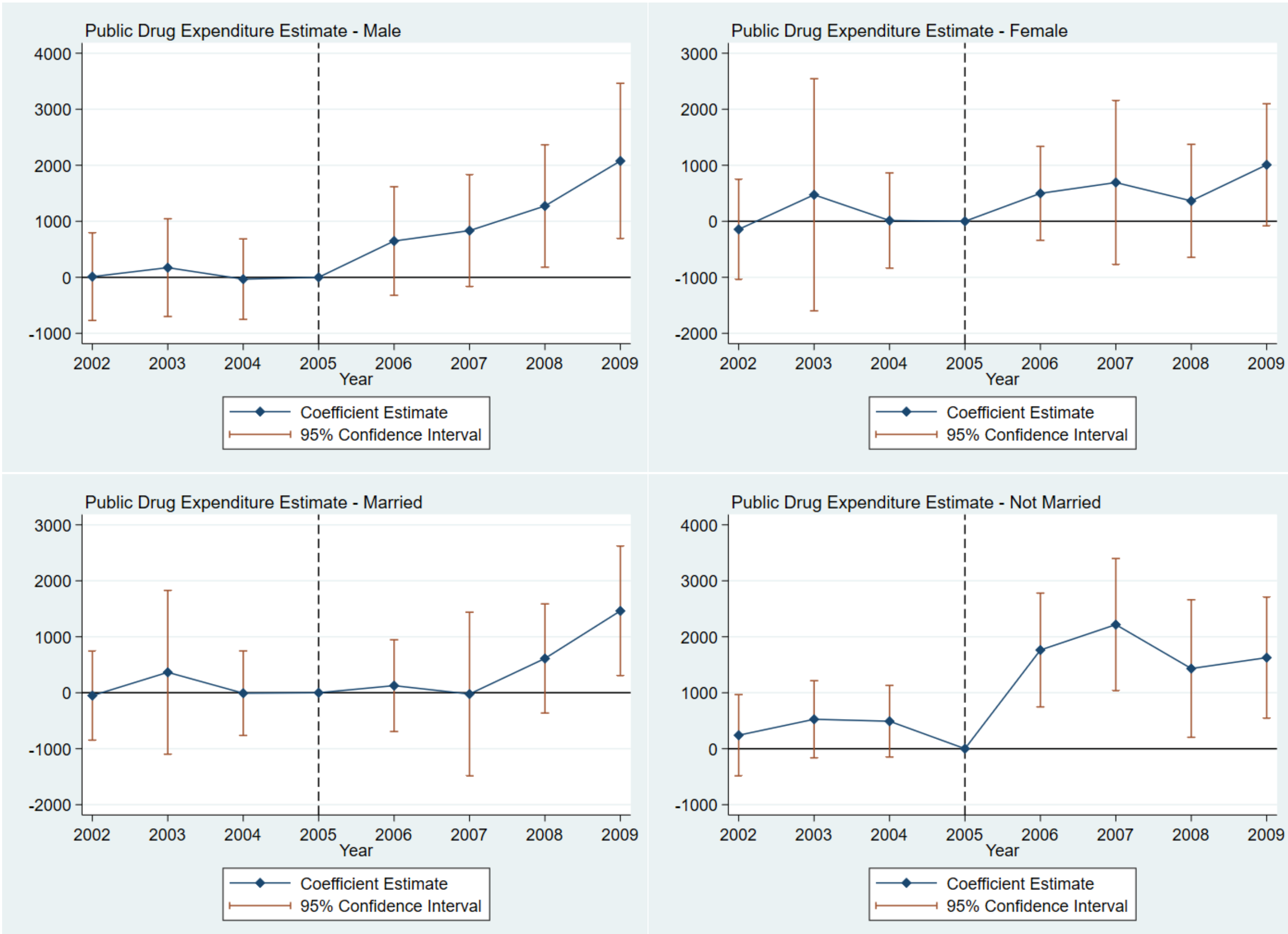
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D11. Event Study - Public Drug Expenditure - By Age and Education



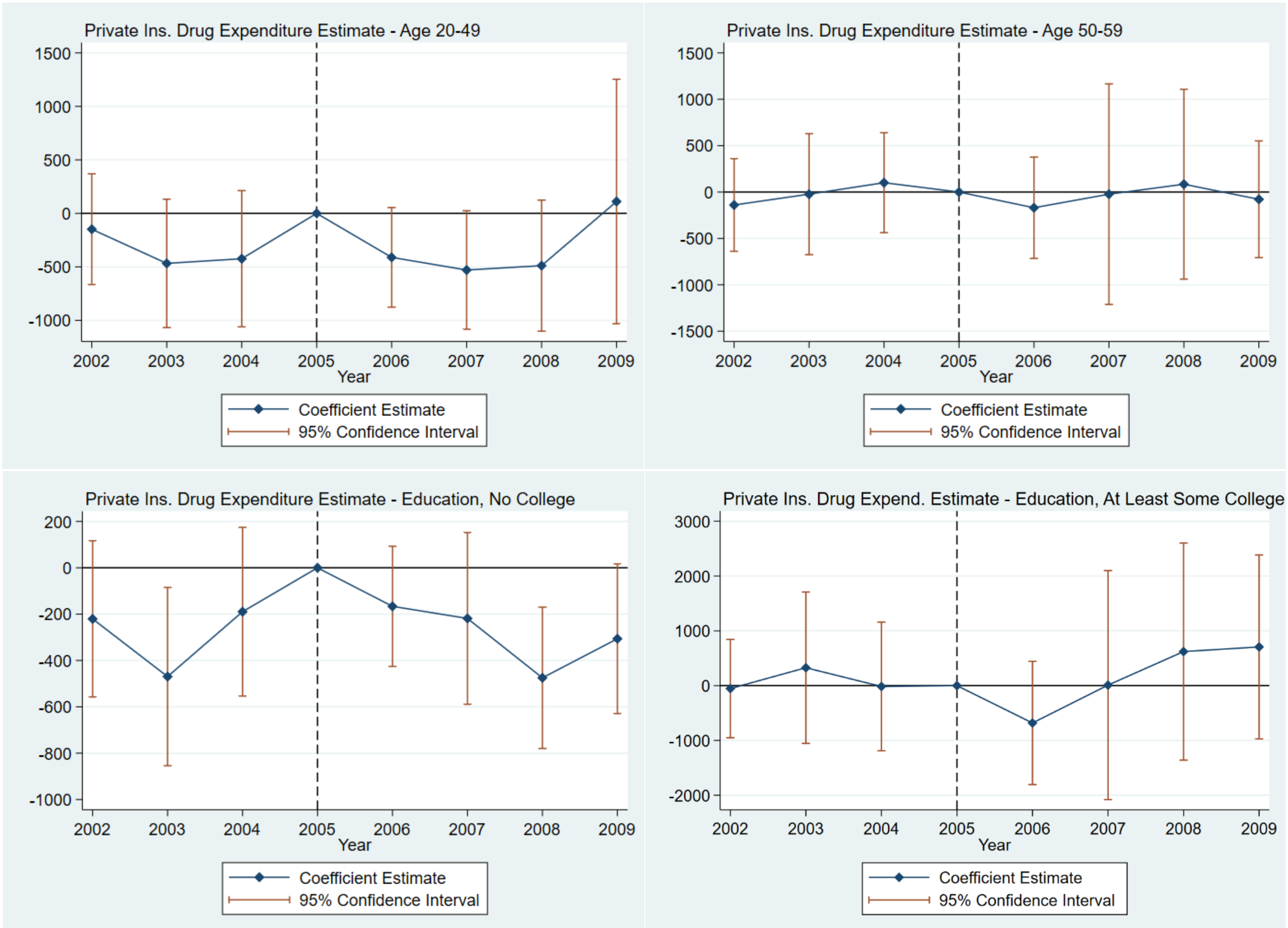
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D12. Event Study - Public Drug Expenditure - By Sex and Marital Status



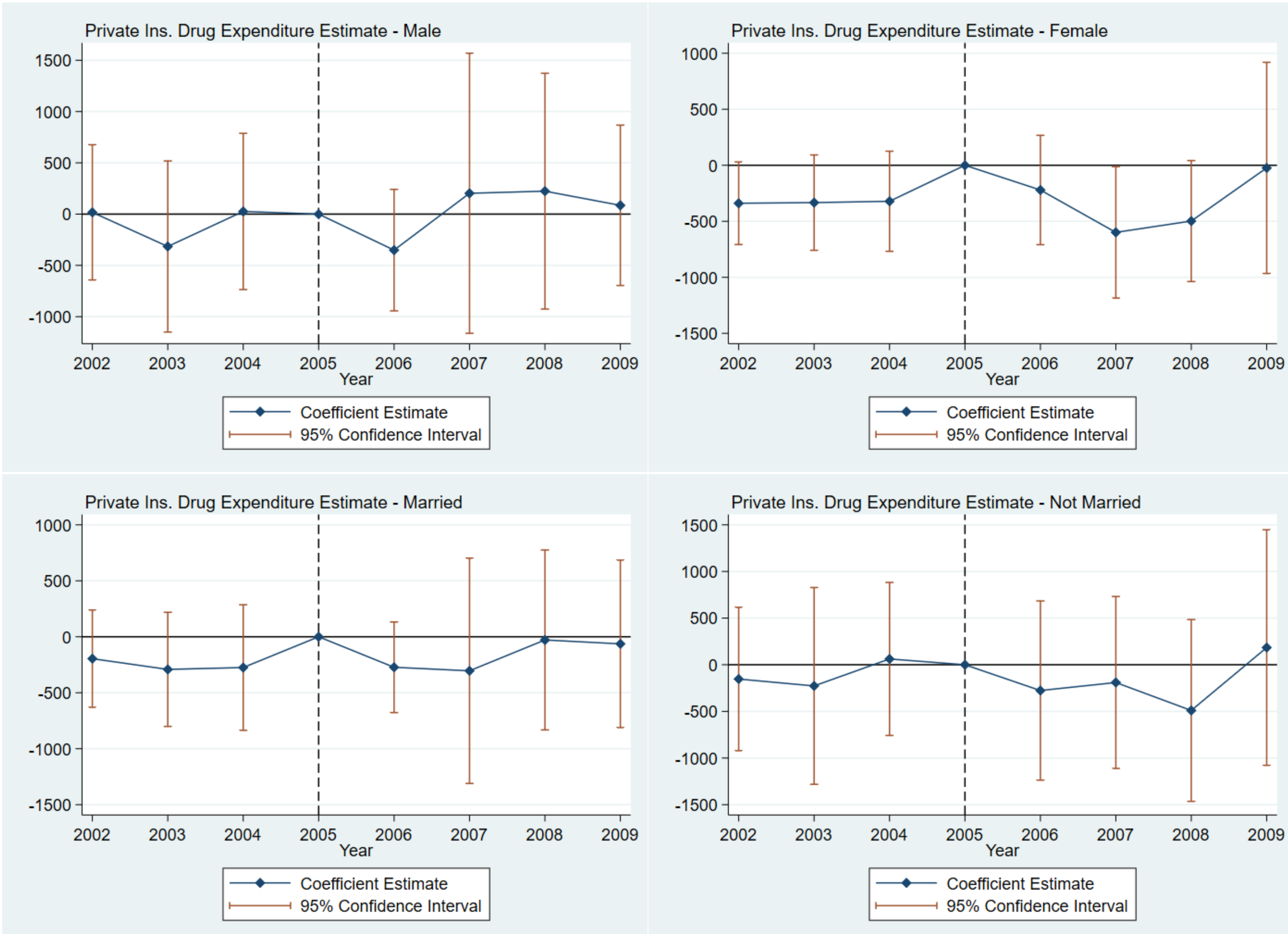
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D13. Event Study - Private Insurance Drug Expenditure - By Age and Education



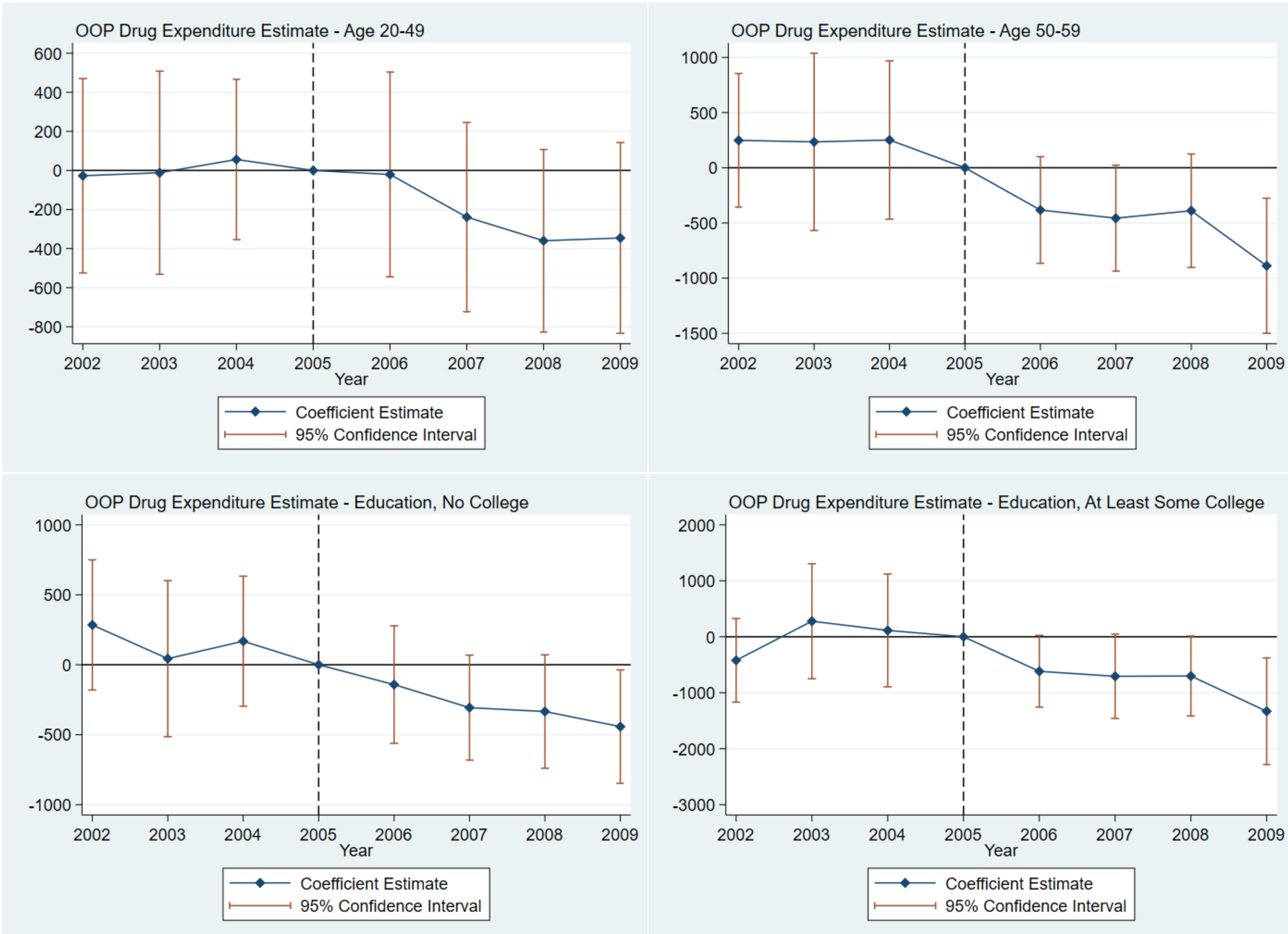
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D14. Event Study - Private Insurance Drug Expenditure - By Sex and Marital Status



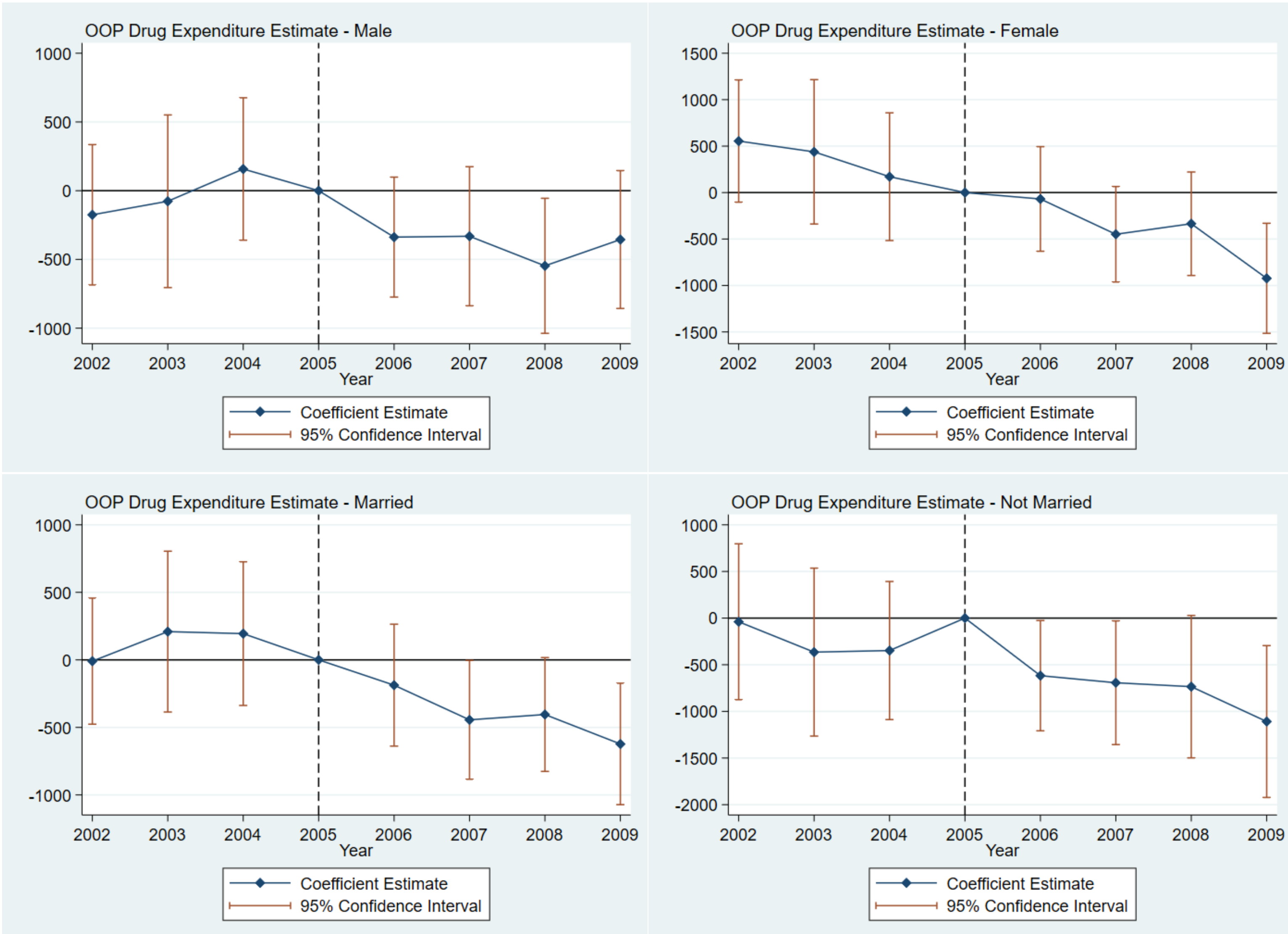
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D15. Event Study - OOP Drug Expenditure - By Age and Education



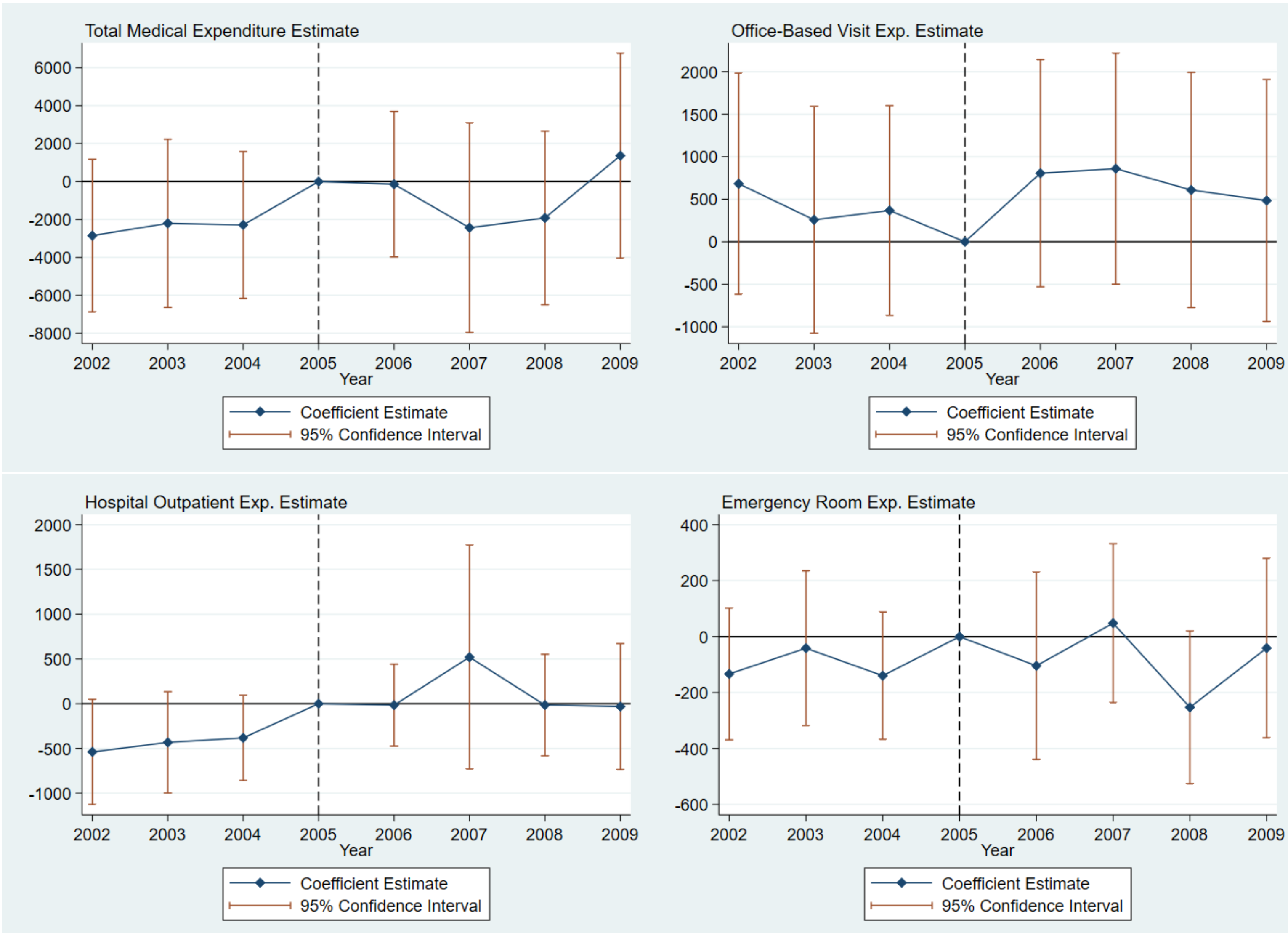
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D16. Event Study - OOP Drug Expenditure - By Sex and Marital Status



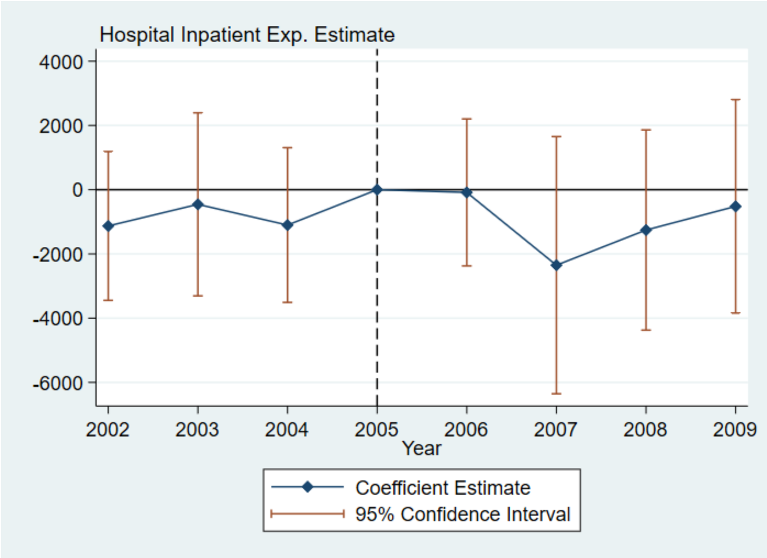
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D17. Event Study - Other Health Care Expenditure 1



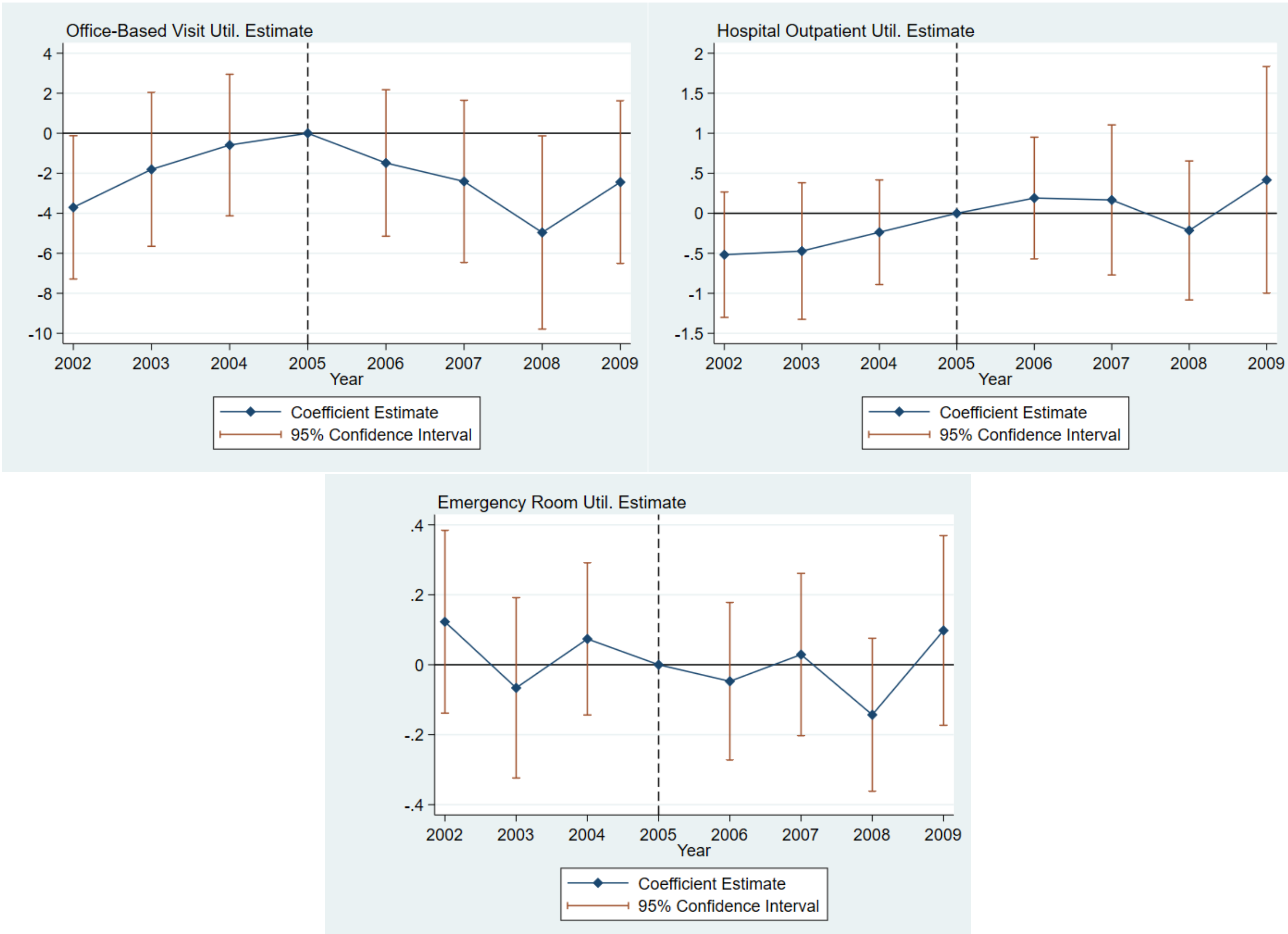
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D18. Event Study - Other Health Care Expenditure 2



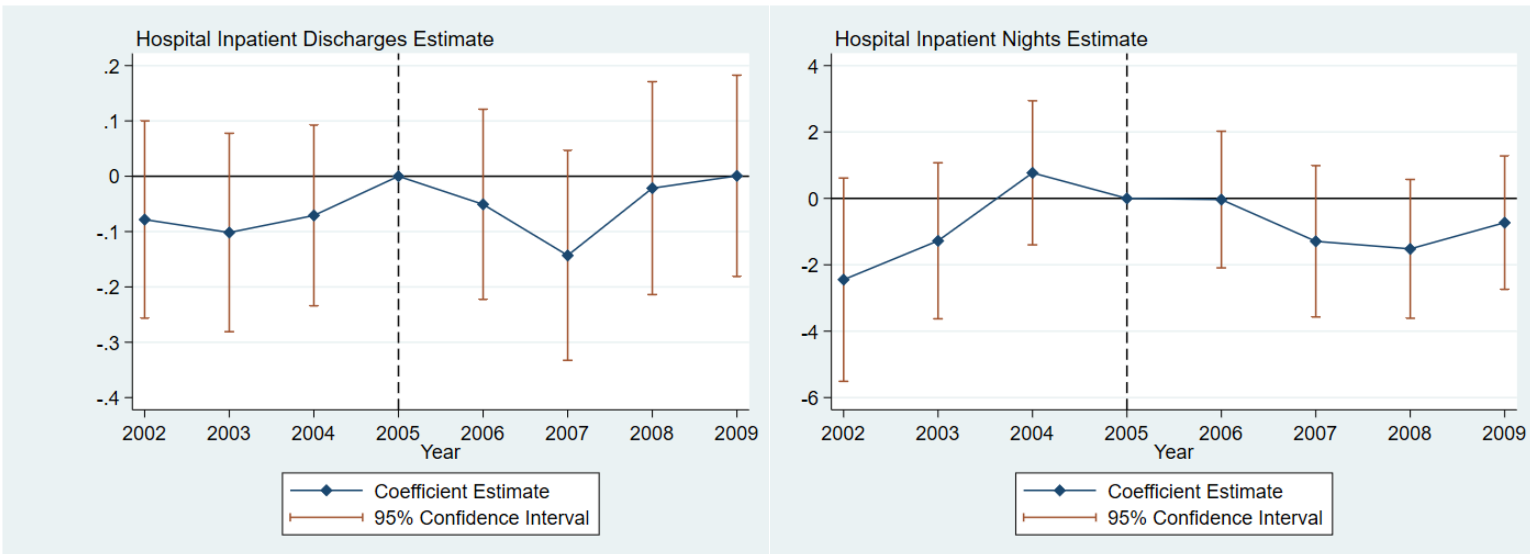
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D19. Event Study - Other Health Care Utilization 1



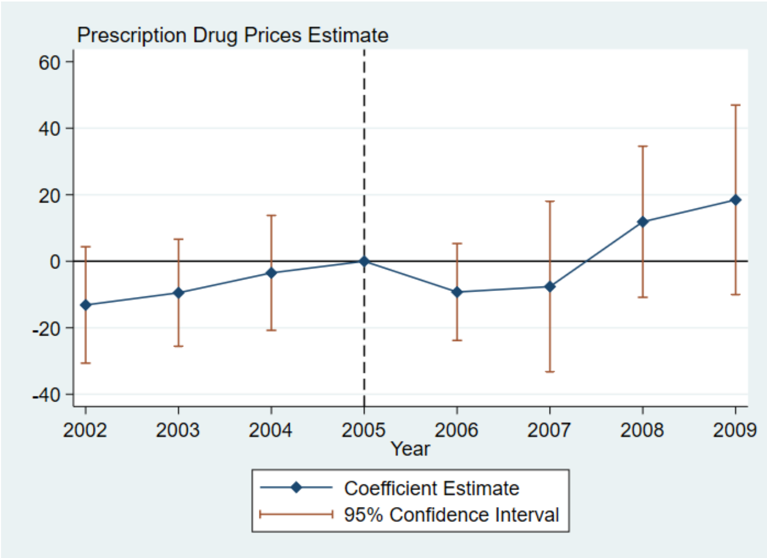
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D20. Event Study - Other Health Care Utilization 2



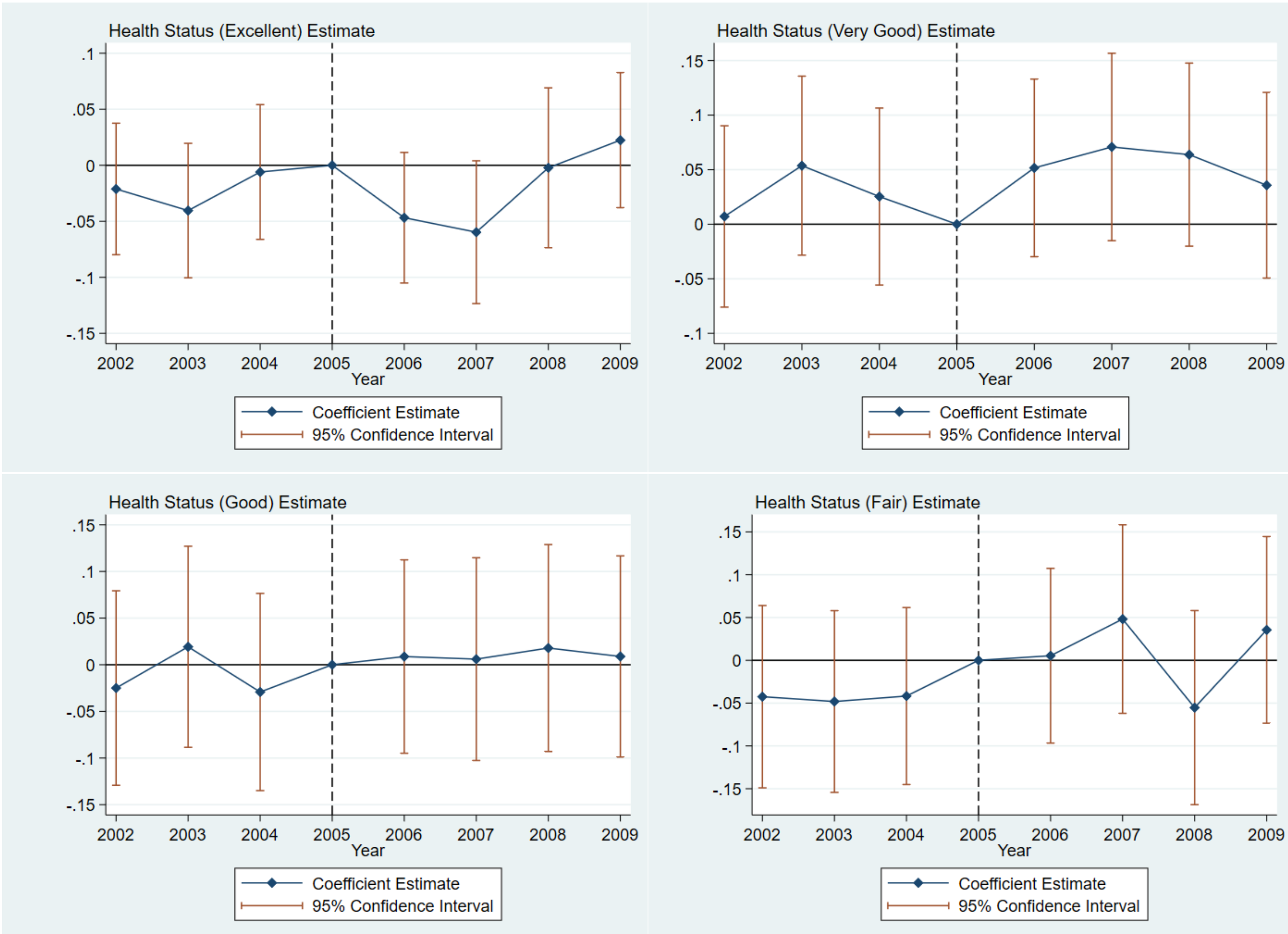
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D21. Event Study - Prescription Drug Prices



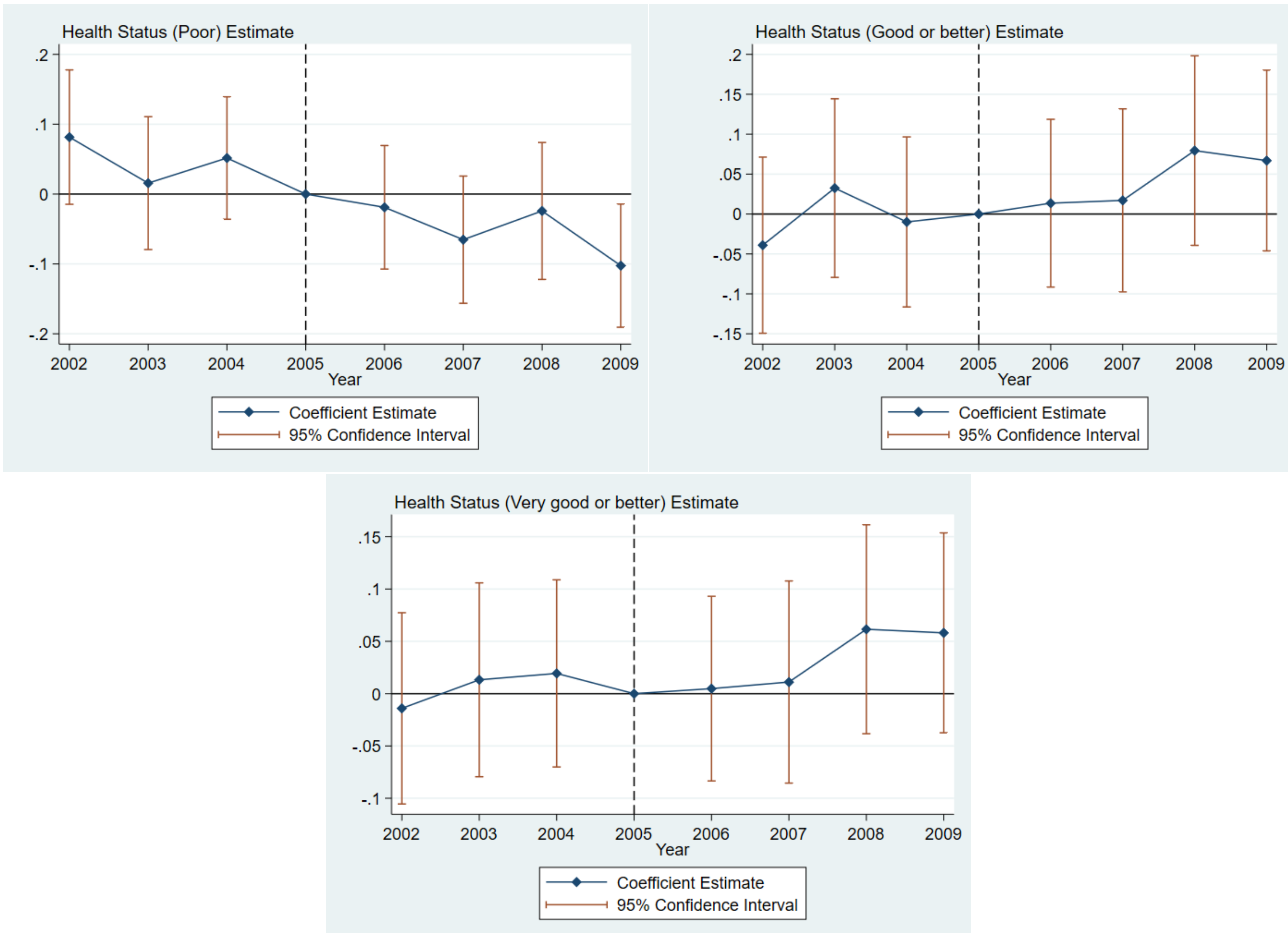
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D22. Event Study - Health Status 1



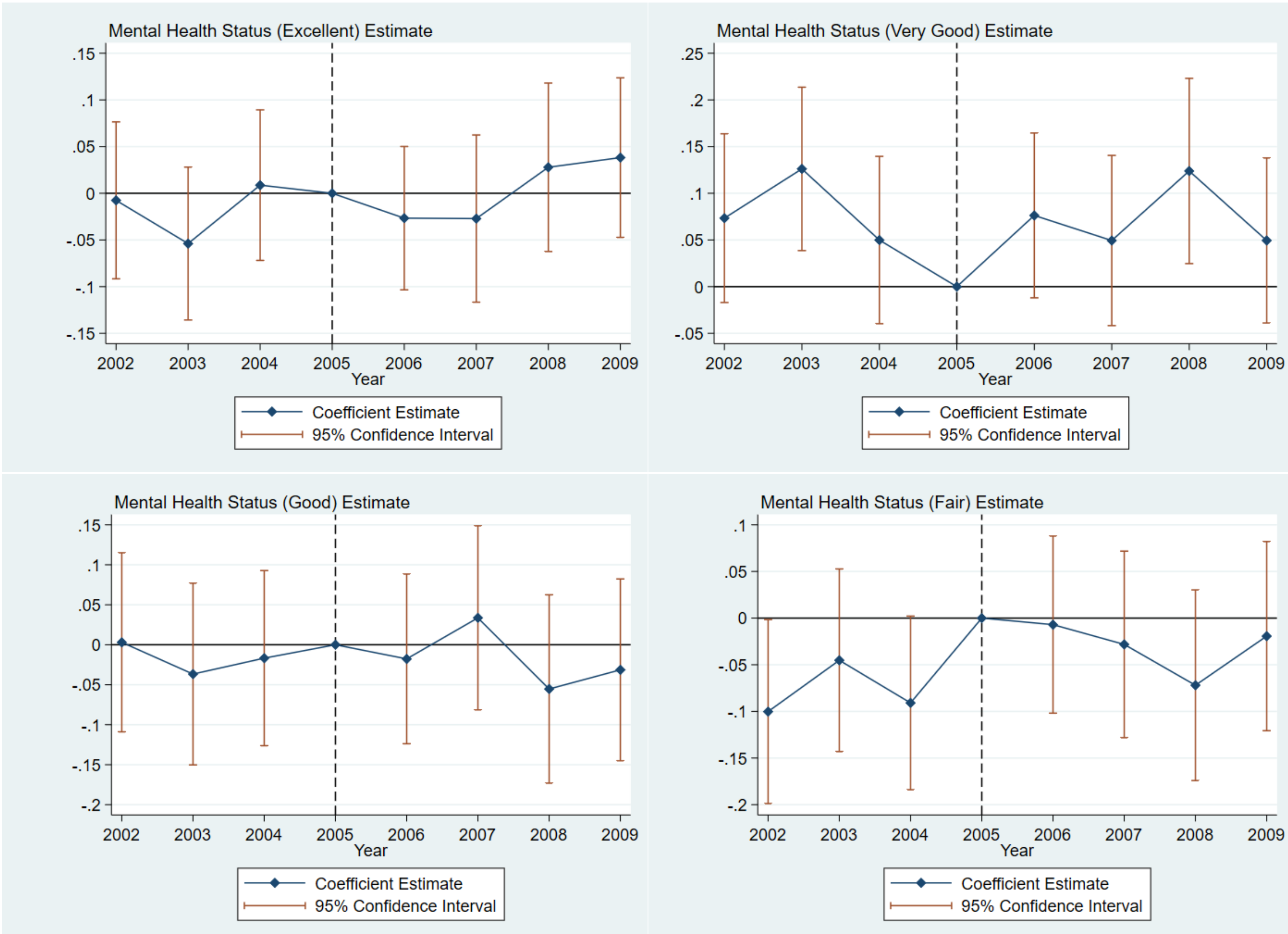
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D23. Event Study - Health Status 2



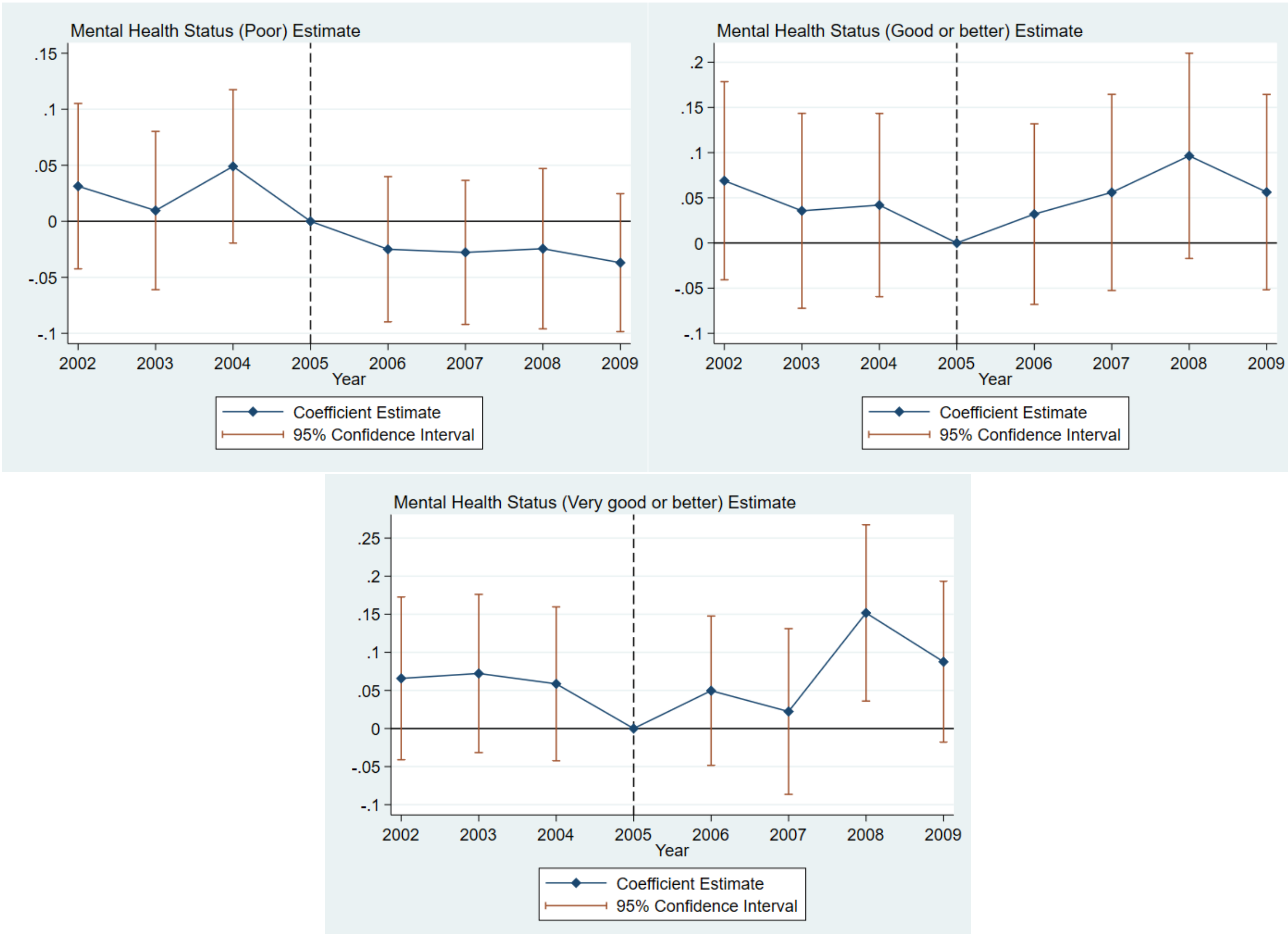
Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D24. Event Study - Mental Health Status 1



Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

Figure D25. Event Study - Mental Health Status 2



Notes: Data from the MEPS for years 2002-2009. Includes SSDI population for ages 20-59, excluding people with chronic kidney disease.

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