Essays in Applied Microeconomics

By

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Abstract

In Chapter 1, I study how asset test elimination of Medicare Savings Programs affect elderly seniors financial difficulty to access health care. In the United States, most elderly seniors are covered by Medicare. However, the original Medicare could incur non-negligible and uncapped out-of-pocket expenditure to the beneficiaries, which could make health care still unaffordable. Medicare Savings Program (MSP) is a Medicaid program that help eligible Medicare beneficiaries to pay their Medicare share cost. Asset test is often the major hurdle to block income eligible seniors to enroll in MSP. Ten states have eliminated the asset test in MSP. I use difference in difference approach to estimate that removing the asset test in MSP increased elderly seniors' Medicaid coverage rate by 19 percent and reduce their financial difficulty to access health care by 8 percent at extensive margin. Event study result shows that in average it took 3 years for the effect to take off. States should consider removing the asset test or make it less restrictive if doing so will make health care more accessible to elderly seniors and reduce states' administrative cost burden.

In Chapter 2, I study how Medicare eligibility at age 65 reduced people's incentive to get Medicaid divorce. To get a divorce, split the joint assets, and allocate most of the assets to the healthy spouse is a strategy to help the sick spouse financially qualify for Medicaid coverage. The exogenous age-based increase in eligibility for Medicare and Medicaid reduces the incentive for people crossing the 65-threshold to implement Medicaid divorce. Using regression discontinuity design, I estimate a 4.1 percent discrete decrease in the prevalence of divorce at the 65-threshold. By examining how the magnitude of the divorce gap is associated with the state-level

variation in Medicaid asset test, I argue that the divorce gap at age 65 measures the reduction in Medicaid divorce. In addition, the heterogeneity analysis indicates that the divorce gap is significantly larger for women, which suggests that Medicaid divorce is more prevalent when the sick spouse is the wife.

In Chapter 3, I study the relationship between technological change and local labor markets. Between 2000 and 2006, the U.S. economy was expanding and the housing market exhibited prosperity. I examine the heterogeneous effect of the housing boom and the Routine Biased Technological Change (RBTC) on the occupational composition of the U.S. labor market during this period. All 3-digit occupations are classified into eight groups based on their task measures and education requirements. I find that the local housing boom boosted the overall local employment level, while the effect of RBTC was concentrated on low-skill occupations. Among the low-skill occupations intensive in routine tasks, the local housing boom increased the local employment share in office administrative support occupations, but had no significant effect on production occupations. At the same time, the RBTC was shifting the low-skill labor force away from these routine occupations to low-skill local service jobs. Moreover, the production workers were losing jobs even when the economy was good, while the employment share in local service occupations maintained strong even after the housing bubble burst.

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Chapter 1

Evaluating the Impact of Asset Test Elimination in Medicare Savings Program

1.1 Introduction

In the United States, elderly seniors age over 65 usually have Medicare health insurance coverage. However, people who have original Medicare as the sole source of health insurance often face non-negligible cost sharing. E.g. there is $1316 annual deductible in Medicare Part A (inpatient hospital insurance), and Medicare Part A has zero coverage for hospital stays beyond the 150th day. Also, Medicare Part B (outpatient medical insurance) has unlimited 20% co-insurance and does not have catastrophic cap. Even though elderly seniors have higher insurance coverage rate (near 100%) than the younger cohorts, they bear much higher out-of-pocket expenditure than the younger cohorts as well (see Figure 1.1). As a consequence, in order to fill the cost sharing gap of original Medicare, Medicare beneficiaries usually have to purchase additional health insurance plans (Medigap supplemental plans, Medicare Advantage, etc) from the private market, or seek help from public health insurance programs.

Medicare Savings Programs (MSP) are state Medicaid programs that help financially poor Medicare beneficiaries to cover the Medicare out-of-pocket expenditure. Despite its name, MSP is a means-tested Medicaid program. Like other Medicaid programs, it is jointly funded and managed by both federal government and state government. People who are Medicare beneficiaries and also have income and asset below certain limits are eligible to enroll.

The MSP income test and asset test vary across states. In most states, the income limit is

100% FPL (Federal Poverty Line), and the asset limit is \$7280 for individuals and \$10930 for couples (in 2015). Asset test is often considered the major barrier to block the income eligible Medicare beneficiaries to enroll in MSP. When people reach their retirement age, it is often the case that they will have low income flow, but have saved some money in retirement account. Compared to the income test, the asset test is more binding for elderly seniors. Researchers have been calling for removing the MSP asset test entirely. Figure 1.2 plots the density of out-of-pocket (OOP) expenditure between two cohorts: (1) Elderly seniors with income below 100% FPL but not covered by Medicaid; (2) Elderly seniors with income above 100% FPL and covered by Medicaid. Clearly, cohort (1) face a more right skewed OOP expenditure distribution. The median annual OOP expenditure of cohort (1) is almost 4 times as that of cohort (2). Asset test might be one of the reasons which blocks some of the people to switch from cohort (1) to cohort (2).

On the other hand, asset test can incur cost burden to state Medicaid agency, too. To throughly examine each applicants' asset level requires considerable labor effort. Also, states might want to make the eligibility rules in align for different but similar public health insurance programs, so that it is easier to manage and less confusing. Because of various consideration, ten states have removed their MSP asset test.

This paper studies the impact of eliminating MSP asset test. We exploit the state variation of the timing of the asset test removal, and adopt difference-in-difference, event study, and synthetic control methods. We find that states that removed the MSP asset test increased their seniors' Medicaid enrollment by 19 percent, and reduced seniors' financial difficulty to access health care by 8 percent at extensive margin.

After January 2014, in states that have adopted ACA Medicaid expansion, Medicaid asset test is completely canceled for non-elderly adults (age ≤ 64). Besides, the federal asset limit is raised to %138 FPL. Non-elderly adults in these states will find the barrier to qualify for Medicaid is lower than ever before. At the same time, the Medicaid eligibility for elderly seniors did not change. In most states, the MSP income limit is still %100 FPL and the asset test still exits. As a consequence, a 64-year-old Medicaid beneficiary in certain states might find that he/she will lose Medicaid once he/she crosses the age 65 threshold. States should consider relax the financial eligibility of MSP so that the nearly elderly cohorts (age between 60 and 64) did not face coverage reduction and welfare loss when they make the Medicare transition at 65. In fact, asset test elimination in MSP is similar to ACA Medicaid expansion (see Table 1.1).

This is the first paper in the literature to study the impact of asset test elimination in Medicare Savings Programs. Substantial previous literature study ACA Medicaid expansion, which is for non-elderly adults. I show that Medicaid expansion for elderly seniors also have important implication in improving seniors' welfare. And policy makers of public insurance programs can pay more attention to the elderly population. The remaining sections of this paper are structured as follows: Section 2 provides more comprehensive details of the institutional backgrounds. Section 3 introduces the data this paper uses. Section 4 introduces the empirical approach and econometric methodology. Section 5 shows the empirical results. Section 6 discusses special cases. Section 7 concludes.

1.2 Background

1.2.1 Original Medicare

Medicare is a universal federal social insurance program. Medicare is closely related to Social Security program. People who have paid Medicare taxes for at least 10 years when they were working, are automatically eligible for Medicare Part A (inpatient hospital insurance) without paying premium when they turn into 65 years old. Eligible seniors can also choose to purchase Part B (outpatient medical care), which charges $134 monthly premium. Part A and Part B are called original Medicare.

The cost sharing of original Medicare is infamously expensive and uncapped. In Medicare Part A, there is $1316 annual deductible for the first 60 days of hospital stays. No coverage is provided before the deductible is met. The co-pay is $332 per day for day 61-90, and $658 per day for day 91-150. If the Medicaid beneficiary still needs hospital care beyond day 150, no coverage is provided. Part A can also cover skilled nursing home care. There are no deductible and co-pay for the first 20 days of skilled nursing care. But it incurs \$164.5 co-pay per day for day 21-100. Also, Part B does not cover nursing home care beyond day 100. As for Part B, after \$134 annual deductible is met, there is %20 co-insurance for each Medical care. The co-insurance share is fixed and uncapped.

As indicated in Figure 1.1, although elderly senior cohorts have almost 100% universal health insurance coverage rate because of Medicare, their annual out-of-pocket (OOP) expenditure is nearly four times as large as those of the younger cohorts. In order to fill the cost-sharing hole, elderly seniors can purchase additional Medigap supplemental insurance, which provides a broader range of coverage and lower cost sharing. Alternatively, Medicaid is another option if the senior is eligible.

1.2.2 Medicaid and Medicare Savings Programs

Elderly seniors who are financially poor can also qualify for Medicaid. Unlike Medicare, Medicaid consists of many means-tested programs. Medicaid is jointly funded by federal government and state government, and mainly managed by states. Thus the eligibility rules and coverage details hugely vary across states. In summary, Medicaid provides more comprehensive coverage than Medicare, such as dental care, vision care, nursing home care, etc. More importantly, Medicaid can usually help Medicare beneficiaries pay the Medicare out-of-pocket expenditure.

In general, there are three major channels for elderly seniors to enroll in Medicaid program: (1) SSI (Supplemental Security Income) recipients can automatically qualify for Medicaid; (2) (Medically needy) Those who need health care in particular months and those whose income will fall below certain limits after deducting the health care expenses from the income; (3) Medicare beneficiaries can enroll in Medicaid through a Medicare Savings Program. Table 1.2 shows the financial eligibility for all these three channels. Among these three channels, Medicare Savings Program (e.g. QMB (Qualified Medicare Beneficiary program)) has the most generous income limit and asset limit. Prior to 2010, the federal asset limit is \$4000/\$6000 for Medicare Savings

Program, twice as high as the federal asset limit of the other two channels. Since 2010, the MSP asset limit started to be adjusted to inflation, which further enlarge the gap. For example, the MSP asset limit was \$7280/\$10930, while the asset limit remained to be \$2000/\$3000 for the other two channels. Therefore, Medicare Savings Program is the most accessible channel to enroll in Medicaid for elderly seniors.

Medicare Savings Program is also called “partial Medicaid package", because it only covers Medicare share costs. Unlike full Medicaid, which people have to enroll through the other two channels, Medicare Savings Program does not cover additional health care service that are not covered by Medicare.

There are three different Medicare Savings Programs targeted to elderly seniors: QMB (Qualified Medicare Beneficiary program), SLMB (Specified Low-income Medicare Beneficiar program), and QI (Qualified Individual program). QMB has the most generous coverage: premiums, deductibles, coninsurance, and co-payments of both Medicare Part A and Part B. On the other hand, SLMB and QI only covers Part B premiums. As of eligibility, all three programs have the same federal asset limit, but SLMB and QI have slightly higher income limit. In this paper, we will put our emphasis on the asset test elimination of QMB program.

1.2.3 Asset Test Elimination

About thirty years ago, The Omnibus Reconciliation Act of 1986 (OBRA) first introduced the concept of Medicare Savings Program and gave states the option to establish their MSP. The Medicare Catastrophic Coverage Act of 1988 made the option mandatory. Since 1989, all states have their own QMB program. Since then, the federal asset limit had remained to be \$4000/\$6000 and had not changed for nearly 20 years. Because of inflation, the real value of the asset limit actually has been decreasing, which means the asset test was becoming more and more restrictive and binding. In 2010, because of the Medicare Improvements for Patients and Providers Act (MIPPA) of 2008 made the MSP asset limit in align with the asset limit of the Medicare Part D Low Income Subsidy (LIS) program. This act increased the MSP asset limit to \$6600/\$9910.

Throughout the time, ten states have also completely eliminated asset test in their Medicare Savings Programs. In July 1998, Alabama became the first state to remove asset test. After that, Mississippi, Delaware, Arizona, Vermont, Maine, New York, DC, and Connecticut removed the asset test in different timing. Oregon is the last state that have eliminated the asset test so far – They removed the asset test in January 2016.

Eight years after Maine removed asset test, the state government decided to introduce asset test again for their Medicare Savings Program, although their new asset limit is much higher than the federal level ($50000/$70000, liquid asset only). Besides, although Minnesota haven't removed asset test, they increased the asset limit to $10000/$18000 in 2001 and maintained in a higher level than the federal asset limit.

We will study how MSP asset test elimination affected Medicaid enrollment, and whether it reduced elderly seniors' financial difficulty to access health care.

1.3 Data

We draw Medicaid coverage data from Current Population Survey (CPS). CPS is a public available data set that contains state identifier and health insurance information of the individuals. It also contains rich individuals' demographic characteristics such as age. In our analysis, we will restrict the sample to individuals older than 65 (65 included).

Behavioral Risk Factor Surveillance System (BRFSS) is an annual health related phone interview survey. In the survey, each interviewee was asked "Was there a time in the past 12 months when you needed to see a doctor but could not because of cost?" The variable MEDCOST equals 1 if the interviewee answered "Yes" for the above question, MEDCOST equals 0 if the answer was "No". MEDCOST measures people's subjective perception of whether they had financial difficulty to access health care in the given period. BRFSS also includes state identifier, which is suitable for our analysis.

Figure 1.4 and Figure 1.5 plots the treatment status in state-year panel cells. BRFSS data are more incomplete and noisier than CPS data. In certain state-year cells, the MEDCOST questions were not asked at all, thus we will have missing values in these cells. Specifically, the MEDCOST variable is systematically missing in 2001, so we will drop year 2001 in our regression analysis.

1.4 Econometric Method

1.4.1 Difference in Difference

First, we use a difference in difference model to estimate the average treatment effect (ATE) of asset test elimination, and conduct inference about the statistical uncertainty about the parameter estimate. The DID model setup is as follows:

$$Y_{ist} = \alpha_s + \theta_t + \delta D_{st} + X_i\beta + \varepsilon_{ist}$$

Y_{ist} is the outcome variable (Medicaid coverage or MEDCOST) for individual i in state s in year t. D_{st} is the treatment variable in the state-year cell level: $D_{st} = 1$ if MSP asset test is already eliminated in state s in year t; $D_{st} = 0$ if (1) state s is a control group state, or (2) t is a pre-treatment year for a treated group state s. I include dummies α_s to capture state fixed effect and dummies θ_t to capture year fixed effect. X_i are a vector of individual level covariates. δ is the DID parameter of interest.

1.4.2 Event Study

Since we have a long panel data including over 20 years, and there exists variation in the exact treatment time across different treated group states, we adopt a event study model. In the event study model, we can visualize the dynamic treatment effect by years after the treatment. Also we can visualize the pre-trend of the outcome variable in the years just prior to the treatment. The event study model setup is as follows:

$$Y_{ist} = \alpha_s + \theta_t + \sum_{\tau=-5}^{10} \delta_\tau \cdot 1(EventTime_{st} = \tau) + \varepsilon_{ist}$$

Y_{ist} is the outcome variable (Medicaid coverage or MEDCOST) for individual i in state s in year t. I include dummies α_s to capture state fixed effect and dummies θ_t to capture year fixed effect. $EventTime_{st}$ measures number of years after or prior to the asset test elimination for state s in year t. δ_τ is the parameter of interest, which captures the difference in the outcome variable τ years relative to the baseline level (the last pre-treatment yaer). Then we can plot the estimated $\hat{\delta}_\tau$ along with their confidence interval as a time series.

1.5 Results

Table 1.5 shows that removing MSP asset test significantly increased Medicaid coverage rate for elderly seniors by 2.19 percentage points in the treated states. Compared to the baseline level 11.5 percentage points (the average Medicaid coverage rate in treated states in pre-treatment period), it accounts for 19 percent increase, which is economically significant, too. After controlling individual covariates, the magnitude of the point estimate is lowered by a little bit to 1.76 percentage points, but is still significant.

Besides, removing asset test significantly reduced MEDCOST issues by 0.43 percentage points (8 percent relative reduction). Since MEDCOST is a "yes or no" binary variable, we can claim that the reduction is at the extensive margin.

Figure 1.6 plots the event study coefficients and their confidence intervals on the Medicaid coverage rate regression. Three years after the asset test elimination, the Medicaid coverage rate started to increase to a much higher level. Figure 1.7 plots the event study coefficients for MEDCOST. The MEDCOST issues started to significantly decreased also three years after the asset test elimination, which matches the previous findings in Medicaid coverage rate.

1.6 Discussion

1.6.1 Bring back the Asset Test

Maine is the only state that brought the asset test back after removing it. We are interested to see if bringing back the asset test would offset the previous effect of increasing Medicaid coverage rate and reducing financial difficulty to access health care. So we will look at Maine as a special case study. In the previous DID model, we set $D_{st} = 1$ for Maine between 2006 and 2013, and set $D_{st} = 0$ for Maine after 2014. Now we set D_{st} always equals 1 for Maine after 2006, but add an interaction term $D_{st} \cdot 1(s = Maine) \cdot (t \geq 2014)$. The new difference-in-difference-in-difference (DDD) type model is as follows:

$$Y_{ist} = \alpha_s + \theta_t + \delta_1 D_{st} + \delta_2 D_{st} \cdot 1(s = Maine) \cdot (t \geq 2014) + \varepsilon_{ist}$$

δ_2 is the DDD parameter. It captures the effect of Maine bring back asset test in 2014. Table 1.6 shows that $\hat{\delta}_2$ is estimated -4.94 percentage points for Medicaid coverage, which implies adding the asset test potentially reduced the Medicaid coverage rate by 4.94 percentage points. Relative to the baseline level for Maine in 2013 (17.68 percentage points), it accounts for a 28 percent decrease. On the other hand, the DDD estimate for MEDCOST is insignificant.

The new MSP asset limit in Maine is \$50000/\$70000 liquid asset, which is much higher than the federal level. A possible explanation for the above estimates is that the new asset test only ruled out those MSP enrollees who could have afford health care by themselves if not covered by MSP.

1.6.2 Increase the Asset Limit in Control States

In 2010, the federal MSP asset limit was raised from \$4000/\$6000 to \$6600/\$9910 and became inflation adjusted thereafter. The increase of federal asset limit would shrink the gap between the control states and treated states. We are interested to see if the closing gap also alleviated the impact of asset test elimination. We set up a new DDD model:

$$Y_{ist} = \alpha_s + \theta_t + \delta_1 D_{st} \cdot (t < 2010) + \delta_2 D_{st} \cdot (t \geq 2010) + \varepsilon_{ist}$$

Here we split the post-treatment period into two subperiods to estimate: (1) The treatment effect in the pre-2010 period; and (2) The treatment effect in the post-2010 period. δ_1 and δ_2 capture these two effects.

Table 1.7 reports the result. The average treatment effect on Medicaid coverage rate in all post-treatment periods is 2.19 percentage points. The treatment effect in pre-2010 period is 2.40 percentage points, and the treatment effect in post-2010 period is 2.10 percentage points. Both of them are significant, but the point estimate is larger in pre-2010 period than in post-2010 period.

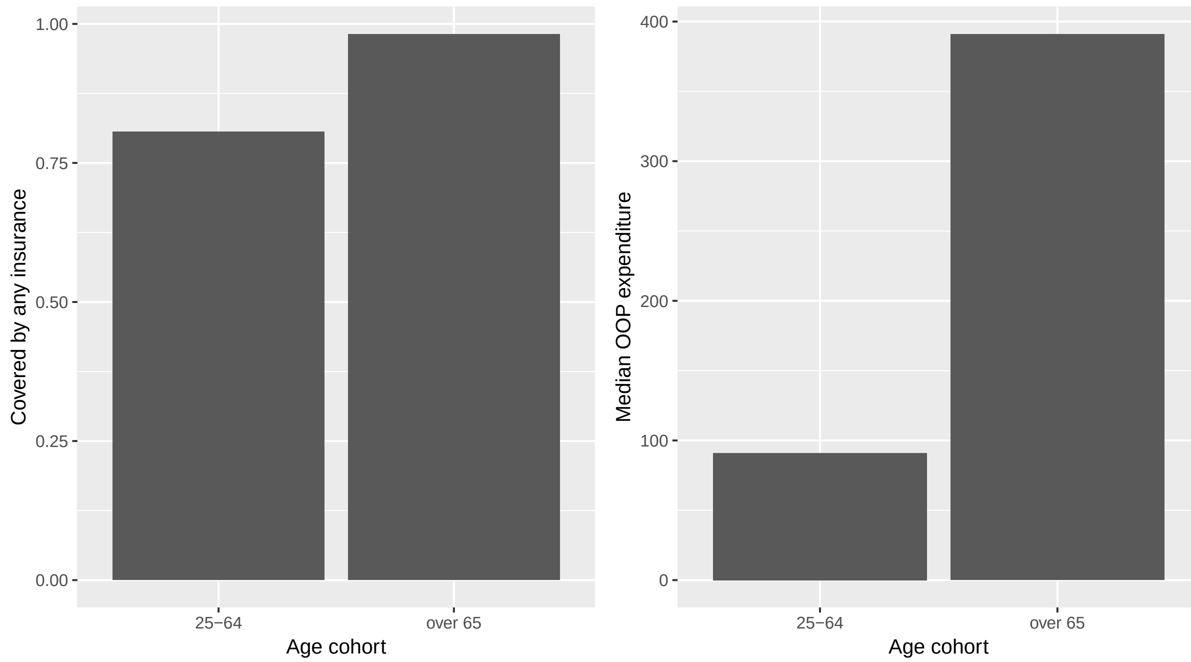
On the other hand, asset test elimination reduced the MEDCOST issues by 1.05 percentage points in pre-2010 period, which is of a much larger magnitude than the average effect over all time (-0.43 percentage points). However, after 2010, there is no significant difference between the treated states and control states.

1.7 Conclusion

In summary, removing asset test in Medicare Savings Program increase the elderly seniors' Medicaid coverage rate by 19 percent and reduced elderly seniors' financial difficulty to access health care by 8 percent. If asset test also bears administrative cost burden to those states still keep the asset test, then those states should consider removing the asset test as well.

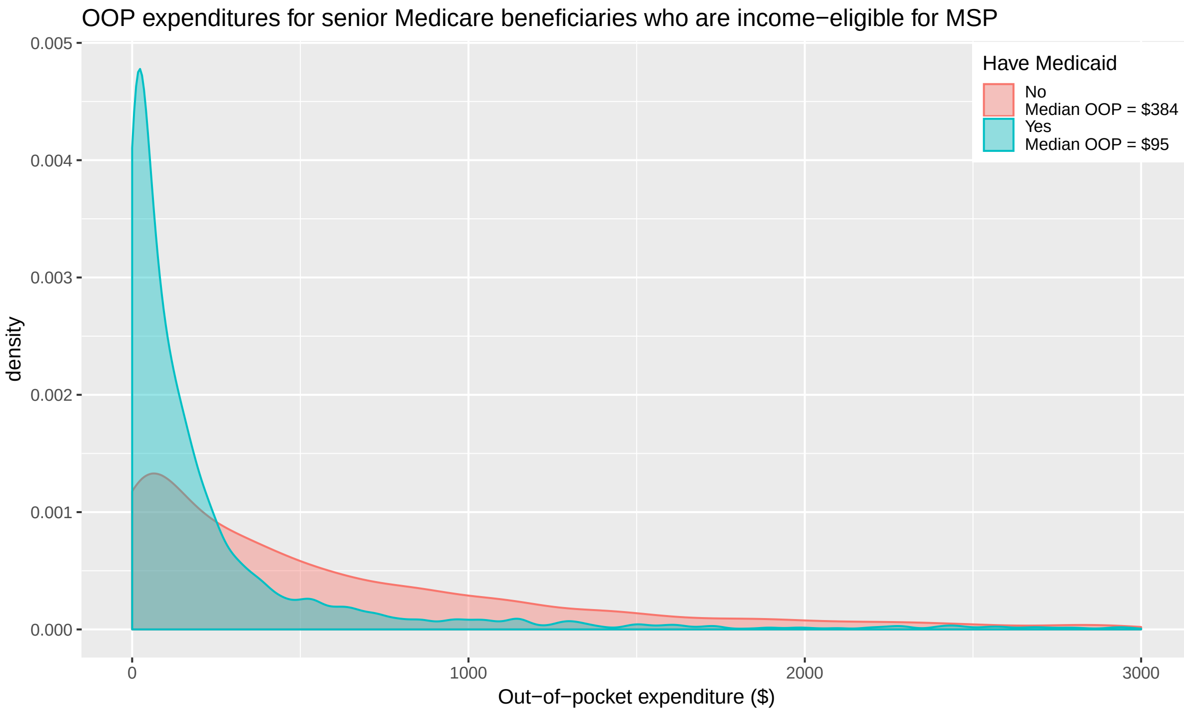
Connecticut, a state that has removed MSP asset test, faced a budget problem in Medicaid expenditure and was discussing to introduce asset test back to the MSP. But eventually this proposal did not pass in the state legislature. Back into 2014, Maine proposed to cut the Medicaid budget for young adults (19-20 years old) and elderly seniors. Congress rejected the proposal to cut budget for young adults but approved to proposal for elderly seniors. That's why Maine introduced asset test back for MSP. We should pay more attention to seniors' welfare as well.

Figure 1.1: Insurance Coverage Rate and Median Annual Out-of-pocket Expenditure by Age Cohort



Data source: 2010-2013 Current Population Survey; 2010-2015 Medical Expenditure Panel Survey

Figure 1.2: Density of Out-of-pocket Expenditure



Data

source: 2010-2015 Medical Expenditure Panel Survey

Figure 1.3: MSP Asset Limit

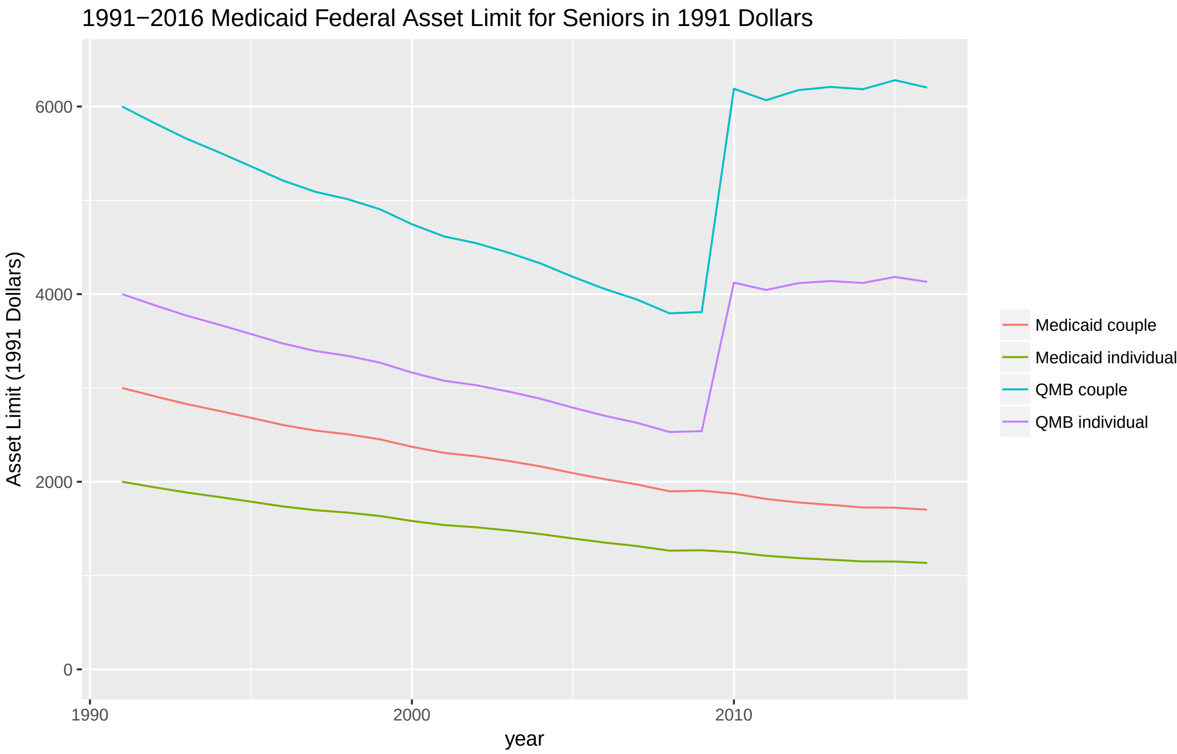


Figure 1.4: State-year Panel of Treatment Status in CPS data

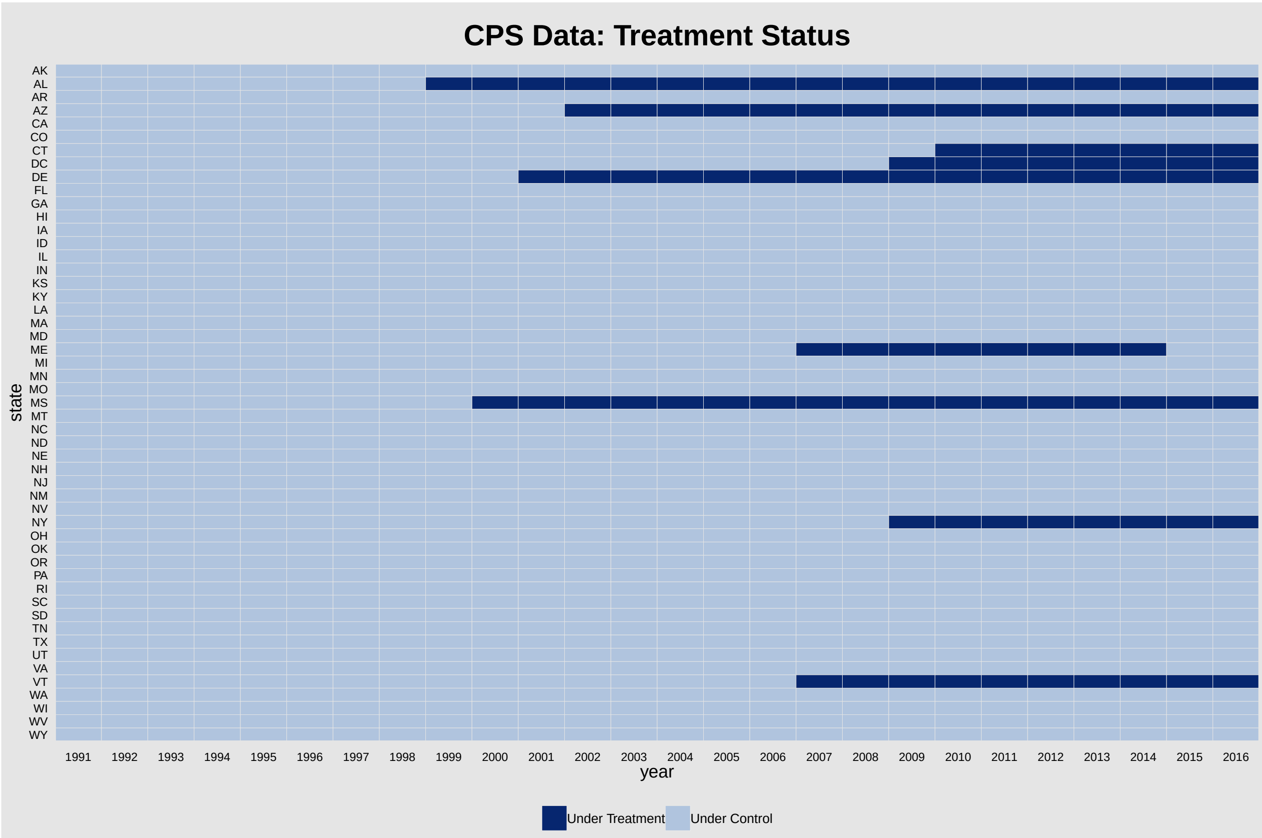


Figure 1.5: State-year Panel of Treatment Status in BRFSS data

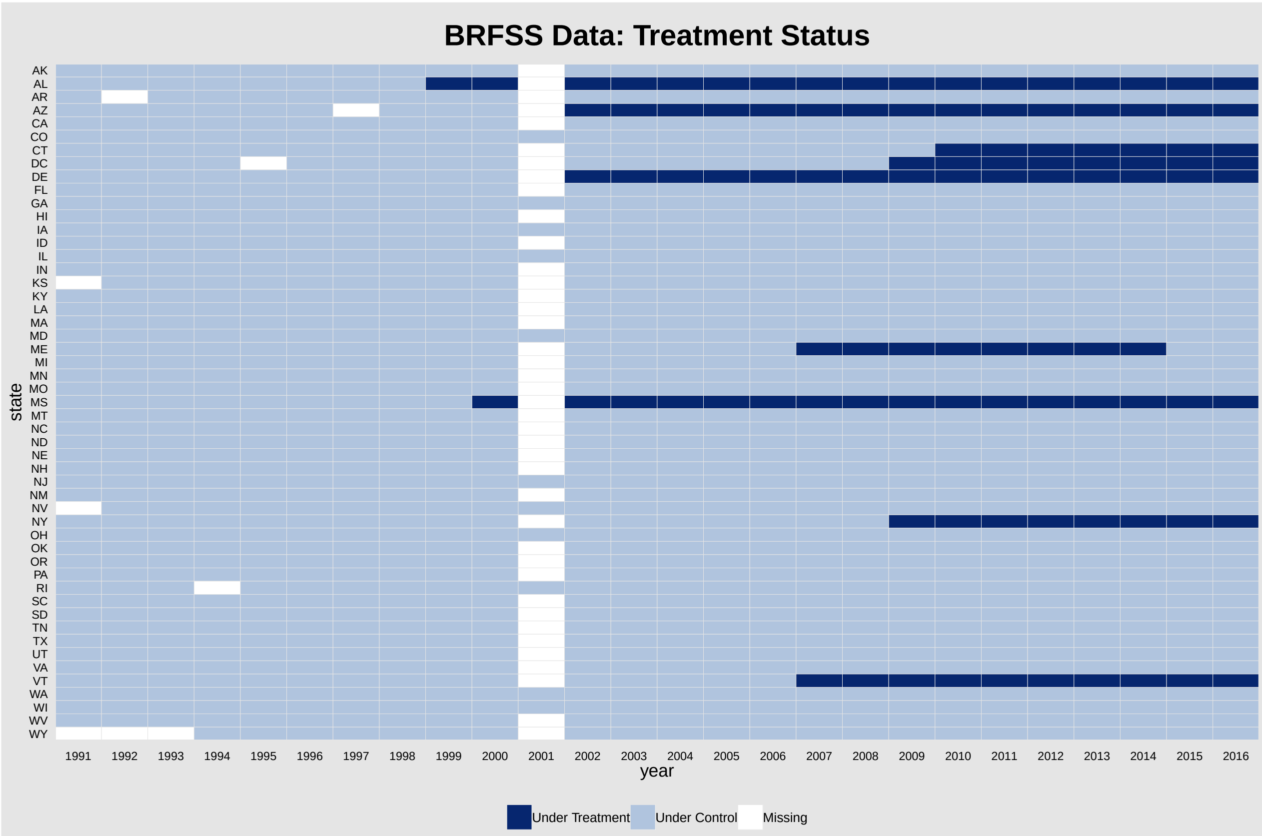


Figure 1.6: Event Study Result of Medicaid Coverage Rate

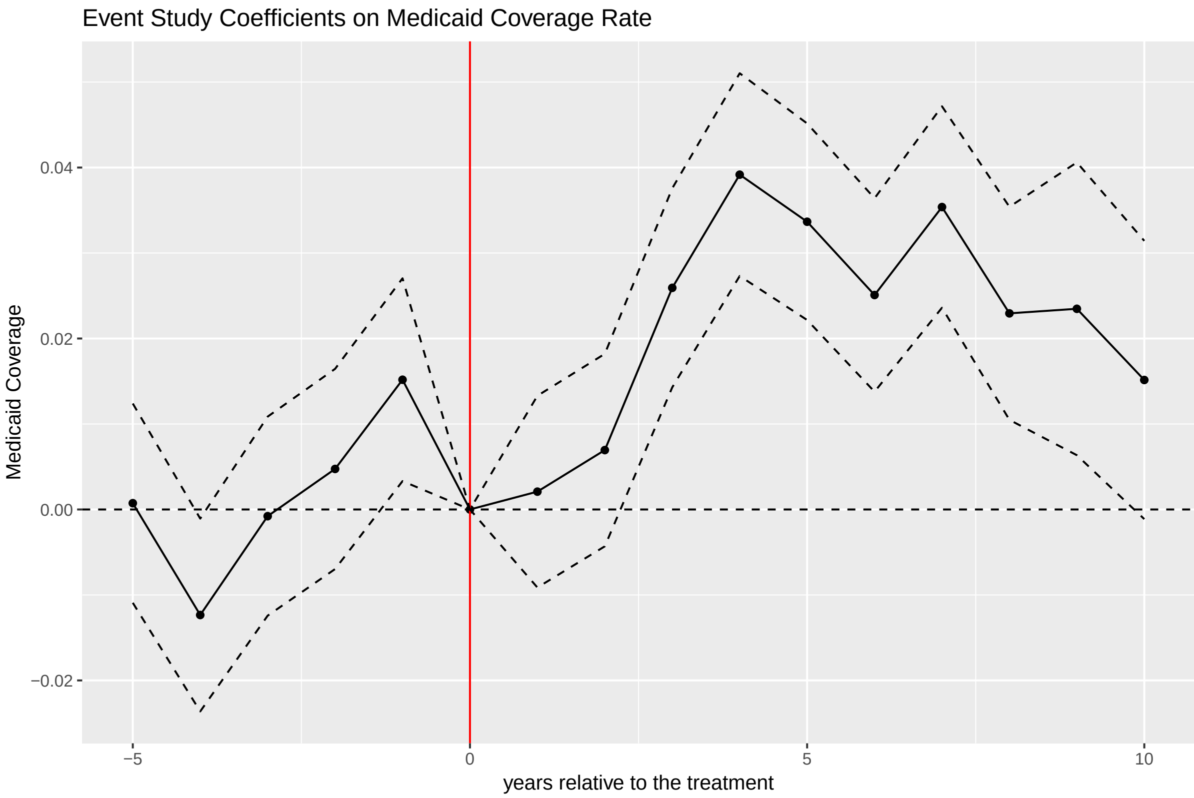


Figure 1.7: Event Study Result of MEDCOST

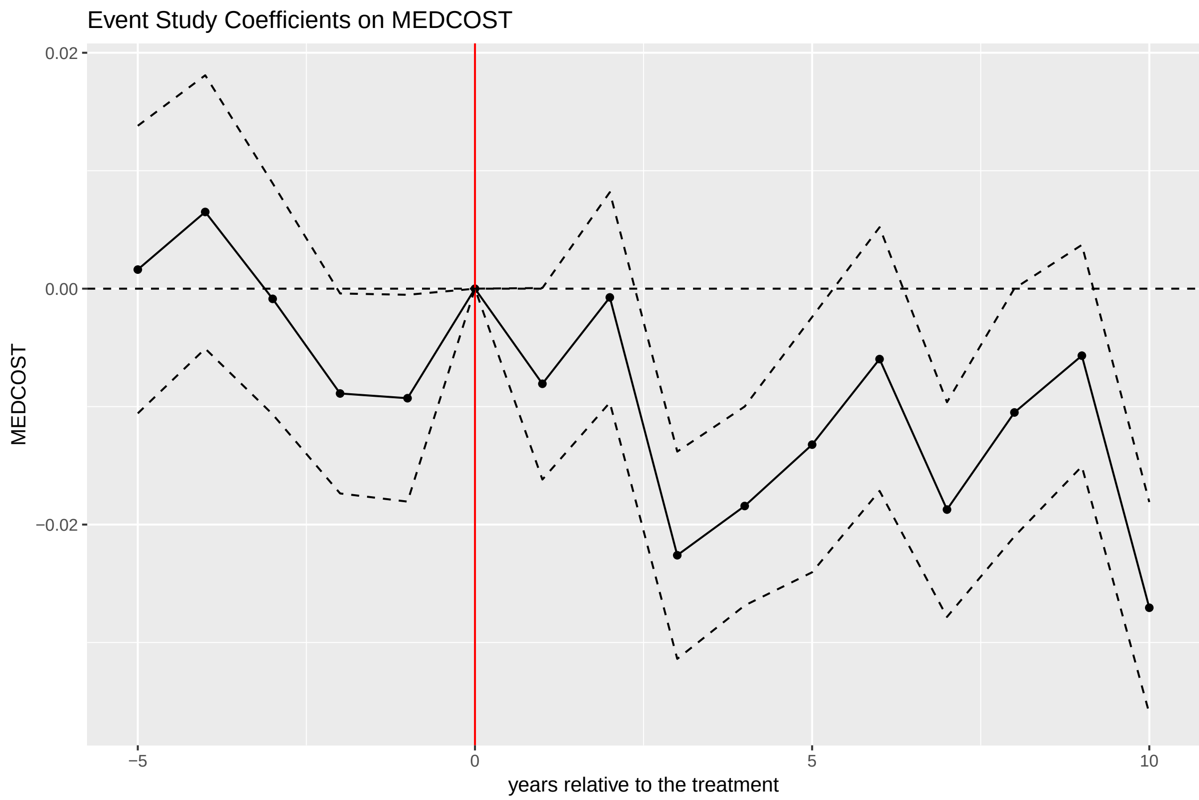


Table 1.1: Comparison between ACA Medicaid Expansion and MSP Asset Test Elimination

	2014 ACA Medicaid expansion	MSP asset test elimination
Age cohort	Non-elderly ($\leq$65)	Elderly seniors ($\geq$65)
Range of expansion	Expanded eligibility groups; Increased income limit; Removed asset test	Removed asset test
Timeline	2014 - current	1998 - current
# adopted states	34	10
Led by federal act?	Yes	No

Table 1.2: Medicaid Eligibility for Seniors

	SSI	Medically Needy[1]	QMB
Income limit (%FPL)			
Federal	73%	NA	100%
State	52% - 100%	10% - 110%	100% - 300%
Asset limit			
Federal	\$2000/\$3000	\$2000/\$3000	\$4000/\$6000[2]

Source: Kaiser Family Foundation. 2015 income limit data for MN and QMB; 2017 data for SSI.

1. As of 2015, 33 states have Medically Needy program.

2. Adapted to higher asset limit in line with Medicare Part D LIS program after 2010. In 2015 it is \$7280/\$10930.

Table 1.3: State Variation of QMB Asset Test Elimination Time

State	Time removed
Alabama	1998 July
Mississippi	1999 July
Delaware	2000 May
Arizona[1]	2001 October
Vermont	2006 January
Maine[2]	2006 March
New York	2008 April
DC	2008 November
Connecticut	2009 October
Oregon	2016 January

[1] Arizona also removed asset test for full Medicaid at the same time

[2] Maine introduced back a $50000/$70000 liquid asset limit in January 2014

* Minnesota did not eliminate asset test but have increased the asset limit to $10000/$18000 since 2001 (federal limit was $4000/$6000).

Table 1.4: Eligibility and Coverage of Medicare Savings Programs

	Qualified Medicare Beneficiary QMB	Specified Low-income Medicare Beneficiary SLMB	Qualified Individual QI
Coverage	Part A & B premiums, deductibles, coninsurance, co-payments	Part B premiums	Part B premiums
Federal income limit (%FPL)	100%	120%	135%
Federal asset limit[1]	\$4000/\$6000	\$4000/\$6000	\$4000/\$6000
Annual limited quota	No	No	Yes

1. Adapted to higher asset limit in line with Medicare Part D LIS program after 2010.

Table 1.5: Difference-in-Difference Estimates

Dependent variable:	Medicaid coverage		MEDCOST	
	(1)	(2)	(3)	(4)
Post_Treatment	2.19^{***}	1.76^{***}	-0.43^{**}	-0.47^{***}
	(0.25)	(0.24)	(0.21)	(0.11)
Baseline level	11.50	11.50	5.22	5.22
Year FE	x	x	x	x
State FE	x	x	x	x
Clustered SE	x	x	x	x
Controls		x		x
Observations	521204	521204	1921164	1921164

The estimates are reported in terms of percentage points. The estimates are based on pooled 1991-2016 CPS and BRFSS data. Standard errors are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 1.6: DDD Estimates, Effect of Maine Bringing Back Asset Test

Dependent variable:	Medicaid coverage		MEDCOST	
	(1)	(2)	(3)	(4)
Baseline level (pre-elimination)	11.50	11.50	5.22	5.22
δ_1	2.15^{***}	2.19^{***}	-0.40^{***}	-0.43^{**}
	(0.25)	(0.25)	(0.20)	(0.21)
Baseline level (Maine 2013)	17.68		2.44	
δ_2	-4.94^{***}		-0.24	
	(1.23)		(0.19)	
Year FE	x	x	x	x
State FE	x	x	x	x
Clustered SE	x	x	x	x
Specification	DDD	DD	DDD	DD

The estimates are reported in terms of percentage points. The estimates are based on pooled 1991-2016 CPS and BRFSS data. Clustered standard errors are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 1.7: DDD Estimates, Pre-2010 Effects and Post-2010 Effects

Dependent variable:	Medicaid coverage		MEDCOST	
	(1)	(2)	(3)	(4)
δ (average effect)		2.19^{***}		-0.43^{**}
		(0.25)		(0.21)
δ_1 (pre 2010)	2.40^{***}		-1.05^{***}	
	(0.37)		(0.25)	
δ_2 (post 2010)	2.10^{***}		-0.17	
	(0.27)		(0.24)	
Year FE	x	x	x	x
State FE	x	x	x	x
Clustered SE	x	x	x	x
Specification	DDD	DD	DDD	DD

The estimates are reported in terms of percentage points. The estimates are based on pooled 1991-2016 CPS and BRFSS data. Clustered standard errors are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Chapter 2

Does Age-Based Public Health Insurance Eligibility Save Medicaid Divorce? Regression Discontinuity Evidence at Age 65

2.1 Introduction

Consider a couple at their late 50s or early 60s. If one of the spouse suddenly gets chronically sick and needs expensive medical treatments, then the couple have to face large medical bills and increasing health insurance premium. In order to prevent the couple from spending down their retirement savings to the medical bills, they might be advised by their lawyer to implement a Medicaid divorce.[1] After divorce and allocating most of their joint assets to the healthy spouse, the sick spouse then becomes financially poor enough to qualify for Medicaid coverage. Then the sick spouse's medical use will be paid by Medicaid. Many elder law professionals think Medicaid divorce is a strategic option to avoid the increasing medical expenditures accompanied by aging.[2]

However, if the sick spouse is over 65 years old, then Medicaid divorce is less necessary. First, seniors aged over 65 are under the cover of Medicare. Medicare is the largest public health insurance program in the United States. People automatically become eligible for Medicare when they cross the 65-threshold. According to their needs, people can choose to enroll in a combination of affordable health insurance plans within the Medicare systems. Medicare does not charge higher premium or even decline coverage based on health conditions.

[1] Michael L. Olver and Christopher C. Lee, "Medicaid Divorce: An Overview." *Helsell Fetterman*, December 13, 2010

[2] Amy Ziettlow, "Is Divorce the Best Option for Older Americans?" *Huffington Post*, May 16, 2015

Second, “seniors aged over 65" by itself is a Medicaid eligibility category. The financial restriction for Medicaid qualification is more lenient for seniors than for many of the categories of people aged below 65. In many states, the asset limit and income limit are set higher for seniors. As a consequence, after crossing the 65-threshold, it is easier for the sick spouse to show financially poor and meet the Medicaid financial eligibility, even without divorce and asset splitting.

These increases in public health insurance eligibility at age 65 is systematic, exogenous, and purely age based. I hypothesize that the incentive for Medicaid divorce will also systematically decrease at age 65 because of the increasing eligibility. To examine my hypothesis, I use regression discontinuity design with pooled 2008-2015 American Community Survey (ACS) data. Assuming age as an assignment variable, I find a divorce gap at the 65-threshold: Divorce rate (the prevalence of divorce) discretely jump down by 0.7 percentage points at age 65, which accounts for a 4.1 percent decrease.

In the literature, many papers exploit the age-based and birth-date-based variation in health insurance eligibility and use regression discontinuity design the study the impact of health insurance coverage. Among many of the papers, Card, Dobkin and Maestas (2008), Card, Dobkin and Maestas (2009) are the most related to my research. They investigate the impact of the universal coverage of Medicare at 65-threshold on medical utilization and mortality. But they do not take into consideration that the eligibility for Medicaid also increases at the 65-threshold. Anderson, Dobkin and Gross (2012) find that the young adults crossing the 19-threshold “age out" of their parents’ insurance plans, which leads to reduction in ED visits and inpatient hospital admissions. More broadly, Carpenter and Dobkin (2009) exploit the minimum drinking age threshold at 21 and find legal access to alcohol increased alcohol related death among young adults.

To my best knowledge, my paper is the first to use regression discontinuity design to exploit the age based eligibility for health insurance and study its impact on divorce behavior and family structure. Chen (2017) uses difference-in-difference design and finds that Medicare unlocks the “marriage lock" of the spousal dependent employer-based health insurance. Literature on Medicaid divorce is also rare. Slusky and Ginther (2017) provide quasi-experimental evidence to show that the ACA Medicaid expansion reduced the divorce rate by 5.6 percent in expanded states among 50-64 cohorts.

To accurately measure the quantity of Medicaid divorce is difficult, since people usually do not reveal their true motivation of divorce. It remains to be an open question in the literature. This paper and Slusky and Ginther (2017) try to estimate the change in divorce prevalence due to the exogenous change in public health insurance coverage, under different contexts. I argue that I at least partly capture the "lower bound" of the quantity of Medicaid divorce.

The main purpose of Medicaid divorce is to make the sick spouse to pass the asset test. To validate my argument that the divorce gap at age 65 is the reduction in Medicaid divorce, I further exploit other sources of exogenous state-level variation in asset tests. First, each state has its own Medicare savings programs. Medicare savings program is partial Medicaid benefit package which help financially poor seniors aged over 65 to cover the out-of-pocket (OOP) expenditure of Medicare. In eight states [3], there are no asset tests for these programs. The incentive for post-65 Medicaid divorce should be further reduced in these eight states. I compare the divorce gap in the states that do not impose asset tests for Medicare savings programs with those states do impose, and I do find statistically larger divorce gap in no-test states (1.1 percentage points v.s. 0.5 percentage points). To my best knowledge, my paper is the first in economics literature to study the state-level variation in Medicare savings programs.

Second, 2014 ACA Medicaid expansion reduced the incentive for people aged below 65 to implement Medicaid divorce. This will "close down" the divorce gap. I do find the divorce discontinuity estimate in expanded states after 2014 to be statistically insignificant. The empirical evidence that the magnitude of the age-based divorce gap is associated with the state-level asset tests supports my hypothesis.

Different subgroups might have different degree of willingness to implement Medicaid divorce. This can be reflected in the heterogeneous magnitude of the divorce gap at age 65. My subgroup heterogeneity analysis indicates that the divorce gap is more significant and larger for women

[3] Alabama, Arizona, Connecticut, Delaware, DC, Mississippi, New York, and Vermont

(0.9 percentage points) and African Americans (1.4 percentage points). There are no statistically significant difference between noncollege population and people with a college degree.

Karraker and Latham (2015) uses Health and Retirement Study (HRS) data to study the relation between spouse's physical illness and the subsequent divorce behavior of the couple. Their descriptive analysis shows that wife's illness onset are associated with elevated risk of divorce, while there is no such association between husband's illness and divorce. My finding on the larger divorce gap for women and insignificant divorce gap for men provides indirect explanation to this phenomenon: Medicaid divorce is more prevalent when the wife gets sick.

The remaining parts of this paper are structured as follows: Section 2 elaborates the institutional background of Medicaid divorce and age based increased eligibility for Medicare and Medicaid. Section 3 elaborates my regression discontinuity design and details on econometric methods. Section 4 briefly introduces data. Main empirical results are presented in Section 5. Finally, Section 6 concludes.

2.2 Backgrounds

2.2.1 Medicaid Divorce

Medicaid is a public health insurance program jointly administered and funded by both federal government and states government. The federal Centers for Medicare and Medicaid Services (CMS) monitors the state-run programs and sets up general requirements for service delivery, quality, funding, and eligibility standards. The primary goal of Medicaid is to secure the right of individuals with limited resources to obtain medically necessary health care. It was introduced in 1965 and majorly reformed recently in 2014 under the Affordable Care Act (ACA). Individuals who have financial difficulties and fall in certain categories are eligible for Medicaid coverage. The categories include children, pregnant women, parents, disable individuals, individuals receiving Supplemental Security Income, elderly senior aged over 65, medically needy individuals, and individuals who need long-term care, etc. The precise covered categories and financial eligibility slightly vary from states to states. States have the option to expand the qualified categories. Medicaid covers the recipients' most of the spending on qualifying medical care, like doctor visits and hospital costs, long-term care services in nursing homes, and long-term care services provided at home, such as visiting nurses and assistance with personal care.

Each state sets up its own income test and asset test for Medicaid financial eligibility. Categorically qualifying individuals have to prove they are in financial difficulties by meeting the limit. When it comes to financial eligibility, married couple is counted as a unit, so income and asset jointly held by a couple are taken into consideration. There are special rule for couples to meet these tests.

Some states apply the same income requirement for Medicaid as for Social Security Disability (SSD) benefits. In these states SSD benefit recipients are automatically eligible for Medicaid. In other states, the income requirement is more restrictive. Most states set up the income limit as a certain percentage of Federal Poverty Line (FPL). In most states, the asset limit is $2000 for an individual and $3000 for a couple. Assets that fall into certain categories are exempted, such as principal residence home, one motor vehicle, clothing, furniture, jewelry, prepaid funeral plans, and life insurance, etc. All non-exempted, excess assets of the couple are required to be spent down in order to obtain Medicaid eligibility for either spouse, regardless of whether the asset is registered under the healthy spouse's name or under the sick spouse's name. Therefore, transfer from the sick spouse to the healthy spouse does not work.

Technically, the couple can transfer the excess assets to their children, siblings, parents and relatives so that the excess assets will be ruled out from their account. Then they can fall below the asset limit. However, state will look at all transfers made within five years before the applicant applies for Medicaid. A penalty period when the individuals are temporarily ineligible for Medicaid is determined if suspicious transfers are detected during the five-year look back period. The length of the penalty period depends on the precise amount of the assets being transferred. Therefore, asset transfer might not be the optimal strategy for those whose wealth is far above the limit and have urgent need for Medicaid coverage.

Instead, couples in such situations might be advised by their lawyer and financial planner to implement a divorce. Divorce is a legal way to separate assets between the sick spouse and the healthy spouse. After divorce and allocating most of the assets to the healthy spouse, the sick spouse will be counted as an individual and will have assets below the limit when applying for Medicaid. Such asset separation due to divorce is not subject to the penalty period. At a practical standpoint, such Medicaid divorce can be viewed as a welfare optimization and strategic response to the eligibility policy, rather than end of love, commitment and responsibility.

To implement Medicaid divorce in a legal, efficient manner requires professional expert and specialized knowledge in various areas. A successful Medicaid divorce often relies on the joint effort by an elder law attorney, an estate planner, and a divorce lawyer, etc.

To empirically measure the magnitude of Medicaid divorce is one of the objectives of this paper. In fact, being divorced is positively correlated with having Medicaid. I plot the correlation coefficients between being divorced and being covered by Medicaid among age cohorts in Figure 2.1. We can see a clearly invert U-shape structure. Before 65, the correlation between divorce and being covered by Medicaid is increasing as age increases. The upward trend starts to get steeper since about 50-year-old cohort, and the correlation reaches the peak at 64-cohort. At 65-year-old cohort, the correlation discontinuously drops, then starts to go down. Of course, there might be common confounding factors which affect both divorce status and Medicaid eligibility, so part of the correlation might be spurious. But it still offers suggestive evidence to a possible explanation: as people aging, there is an increasing trend for individuals to implement Medicaid divorce in order to get Medicaid coverage. That's why we see stronger and stronger correlation. But after 65, suddenly people don't need Medicaid divorce any more. So the correlation starts to decline. At a preview of Figure 2.2, we can see a similar picture: The divorce rate also discontinuously drops at 65, then gradually goes down.

2.2.2 Medicare

Medicare, administered solely by federal government, is an age-based public health insurance program. Elderly seniors aged over 65 are automatically eligible for Medicare coverage. Unlike Medicaid, there is no big difference in many of the institutional settings of Medicare across states. Medicare coverage is divided into many parts. Some of them are free, and some of them charge premium and are optional. Elderly seniors who (whose spouse) have been working and paying Medicare taxes for at least 10 years are covered by Medicare Part A without paying premium. Medicare Part A covers inpatient hospital care, skilled nursing facility care, and hospice care. Medicare Part B covers preventive service, clinical research, ambulance service, durable medical equipment (DME), mental health, etc, most of which are in outpatient basis. Typically, people have to pay for Part B. The standard premium in 2017 is $134 per month. Part A and Part B together are usually called “Original Medicare". Both Part A and Part B provide standardized, uniform coverage to each Medicare beneficiaries.

Medicare beneficiaries can also optionally purchase Part D. Part D mostly covers prescription drugs. Unlike Original Medicare, Part D is not standardized. People can choose one of the Part D drug plans depending on their needs. Each drug plan has its own list of covered drugs. The monthly premium also differ among drug plans.

Compared with Medicaid, Medicare is less generous. In fact, the share cost of Medicare is high. For example, in 2017, there is $1316 deductible for a hospital stay of days 1-60. The co-pay for days 61-90 is $322 per day and the co-pay for days 91-150 is $658 per day. There is no deductible and co-pay for the first 20 days of skilled nursing care. But the co-pay is $164.5 per day for days 21-100. The yearly deductible for Medicare Part B is $183. After the deductible is met, people still need to pay 20% co-insurance.

Original Medicare does not include out-of-pocket (OOP) limit. It does not cover nursing home care and custodial care if they are the only medical service needed. For those elderly seniors in great demand for long-term daily care, the coverage of Original Medicare is very limited. Original Medicare beneficiaries still face the stress of high OOP expenditure.

Original Medicare beneficiaries can also optionally purchase Medicare Supplement Insurance (usually called Medigap). Medigap supplements Original Medicare, and pays for the share cost of Original Medicare such as deductibles, co-payment, and co-insurance. Medigap policies are sold by private companies, but they are strictly regulated by federal and states. Companies are prohibited to make extra charge or decline coverage based on client's medical answers, and are prohibited to decline renewing the policy due to health issues. All Medigap policies offer basic standardized benefits, and some provide additional benefits. The main purpose of Medigap is to help beneficiaries to fill in the financial holes of Original Medicare. Some Medigap policies cover all Original Medicare OOP expenditure and provide complete financial security.

Alternatively, Original Medicare beneficiaries can choose to switch and enroll in Medicare Advantage Plan (sometimes called Part C, but it is somewhat misleading since Medicare Advantage Plan and Original Medicare operate in different systems). Medicare Advantage Plan basically covers what is covered by Original Medicare. But people can pay extra premium to obtain extra content, such as out-of-pocket expenditure limit, dental care, vision care, annual physicals, etc. The precise amount of premium differs among plans. The OOP limit is especially useful for those elderly seniors in great demand for regular medical service and treatments. Through the system of Medicare Advantage Plan, beneficiaries must go to only a select network of health care providers.

During 2008-2015, 95.13% of the elderly seniors aged between 65 and 75 receive Medicare. The Medicare coverage rate jumps from only 16.77% for the 64-cohort, to as large as 86.09% for the 65-cohort (based on author's own calculation from ACS data). Medicare does not discriminate pre-existing conditions. To some extent, the Original Medicare is an affordable health insurance plan charges uniform premium on all beneficiaries (Premium differs slightly depending on beneficiary's income status). Therefore, Medicare partly substitutes Medicaid and other private health insurance at age 65. But Original Medicare alone is far from a perfect substitute for Medicaid due to its limited coverage and lack of out-of-pocket expenditure limit. However, the problem of no OOP limit can be mitigated by purchasing Medigap policies or enrolling in Medicare Advantage Plan, at the expense of paying extra but probably still affordable premium.

2.2.3 Dual Eligibility and Medicare Savings Program

After an individual reaches 65, he/she would almost certainly be eligible for Medicare. But the likelihood of obtaining some Medicaid coverage also increases. That is because: First, "elderly seniors aged over 65" by itself is one of the Medicaid recipient categories. Second, the Medicaid eligibility financial limit for elderly seniors is somewhat more lenient than for those who are aged below 65, depending on states. Third, even an elderly senior is financially non-eligible for Medicaid full benefits, he/she might still qualify for a partial Medicaid benefit package.

Those who are eligible for both Medicare and Medicaid are often referred to "dual-eligible" beneficiaries. Dual-eligible beneficiaries receive either Medicaid full benefit package or Medicaid partial benefit package. Full benefit recipients receive the entire range of Medicaid benefits, including those health care service not covered by the Original Medicare such as long-term nursing home care and personal custodial care. Dual eligibility helps fill in the financial holes of Medicare, as the OOP expenditure of the Original Medicare is infamously uncapped. If a certain category of health care service is in the Medicare-Medicaid-dual-covered list, Medicare will pay for the medical bill first, then Medicaid will cover the remaining OOP cost left by Medicare.

Elderly seniors older than 65 who cannot qualify for Medicaid full benefit might still have a chance to enroll in one of the Medicare Savings Programs. Medicare Savings Programs include Qualified Medicare Beneficiary (QMB) Program, Specified Low-Income Medicare Beneficiary (SLMB) Program, Qualifying Individual (QI) Program, and Qualified Disabled and Working Individuals (QDWI) Program. Regardless of the name, the benefits of Medicare Savings Programs is actually drawn from Medicaid. So there is slight difference across states in financial eligibility rules and precise benefits. But the difference is somewhat smaller than the difference in normal Medicaid. In general, these Medicare Savings Programs help enrollees pay for their Medicare Part A premium, Part B premium, deductibles, co-payments, and co-insurance. The income and asset limit of these programs are set more lenient than the limit for the Medicaid full benefit package. For example, the QI Program covers individuals whose household income up to 135% FPL. More importantly, in Alabama, Arizona, Connecticut, Delaware, DC, Mississippi, New York, and

Vermont, there are no asset limits for participating in these programs.

The relaxation of Medicaid eligibility requirement at age 65 helps fill in the financial holes of Medicare and reimburse the expenditure on medical bills. Based on author's own calculation with ACS data, the share of individuals having Medicaid coverage is 12.13% among 65-cohort during 2008-2015. The combination of Medicare and Medicaid makes elderly seniors less necessary to implement Medicaid divorce. In those states where no asset test is imposed for Medicare Savings Program, the incentive for post-65 Medicaid divorce is further reduced.

2.2.4 Affordable Care Act and Medicaid Expansion

The Patient Protection and Affordable Care Act (ACA) was signed into law in 2010. Many of the policies became effective since 2014. The federal and state government established health insurance exchange, a large online open health insurance marketplace. According to the premium and out-of-pocket spending requirement, the health insurance plans sold in the exchange are categorized into four tiers: bronze, silver, gold, and platinum. All tires of the plans offer the essential health benefits. Within each tier, the premium must be determined solely on the basis of age and residence location. Insurance companies in the exchange are prohibited to decline coverage or charge extra premium due to pre-existing conditions. The maximum premium the insurance companies are allowed to charge the oldest age group cannot exceed three times of the premium charged on the youngest age group. What's more, each health insurance plan must contain maximum out-of-pocket (MOOP) payment cap. Once the annual MOOP cap is reached, the insurance company must pay the remaining costs.

In addition to the reform of health insurance market, ACA also expanded Medicaid. The decision of whether joining the Medicaid expansion was left to states. Federal government is responsible for most of the Medicaid funding in those expanded states for the first few years. The states that expanded Medicaid are required to provide full Medicaid coverage to adults whose income are below 133% of FPL. Asset tests and categorical eligibility were canceled in expanded states. Those states opted out the Medicaid expansion retain asset tests and relatively low income limit.

Federal government also offer tax credit as subsidy to individuals who purchase private health insurance in the exchange, if their income are between 100% FPL (138% FPL if living in non-expanded states) and 400% FPL. The precise amount of subsidy depends on the precise income of the individual. Individuals who fall in this income category are ineligible for Medicaid. But the tax subsidy fills in the gap financially.

In summary, younger elderly people (aged 50-64) might benefit from ACA. First, affordable health insurance plans are now available in the exchange. The ACA is against discrimination on pre-existing conditions so those who have chronic diseases and need long-term health care now can purchase health insurance in the private market in a relatively cheaper price than before. Second, as long as an individual lives in an expanded states, it is now much easier for him/her to qualify and receive Medicaid in terms of both categorical eligibility and financial eligibility. Because of these benefits, younger elderly people have less incentive and necessity for a Medicaid divorce. I raise a hypothesis that the divorce gap at 65 should be smaller in post-ACA era than in pre-ACA era.

As elaborated above, the existence of asset limit and income limit is the main reason for Medicaid divorce. Thus the Medicaid expansion created a natural experiment. We can compare the divorce gap between expanded states and non-expanded states to infer the effect of the asst test cancellation.

2.2.5 Social Security Retirement Benefit

For individuals born in 1929 or later, as long as they had been working under Social Security for at least 10 years, they have an option to start to claim Social Security Retirement (SSR) benefit 3 months before their 62nd birthday, and start to receive the benefit payment at 62. SSR benefit helps seniors to better plan their post-retirement life. The full retirement age varies from person to person, according to the year of birth. Typically the full retirement age increases as a person was born in a later year. For example, the full retirement age of individuals born in 1937 or earlier is 65. For those who were born in 1960 or later, the full retirement age is 67.

Rigorously speaking, if a person do not claim the SSR payment as early as 62 and wait until he/she reaches the full retirement age, he/she can receive the full amount of SSR benefit. Early application at 62 is subject to a discount. For example, for individual whose full retirement age is 65, if he/she starts to claim SSR payment at 62, then he/she can only receive 80% of the full monthly benefit for the rest of his/her life. Since people have different retirement plan and different life expectancy, they choose the starting age of claiming SSR benefit strategically.

After an individual starts to receive benefits, his/her spouse who are aged over 62 can also apply for at most one half of the same benefits, even if the spouse has not established sufficient working history. However, the spouse must be married to the benefit recipient for at least one year before the spouse qualify for the benefit. In addition, individuals who lack working history and are currently divorced can also receive SSR benefits based on the working record of the ex-spouse. It requires that the former marriage with the ex-spouse must last for at least 10 years.

The rules of claiming spouse dependent SSR benefits and ex-spouse dependent benefits should not cause a divorce gap at 65. First, people are not encouraged to suddenly want to keep a broken marriage at 65 only because the spouse without working history wants to keep the spouse dependent SSR benefits. As long as the couple have been married for at least 10 years, the no-working spouse can still receive SSR payment in the form of ex-spouse dependent benefits.

Second, there is no large incentive for an immediate remarriage at 65 only because a no-working single individual wants to get spouse dependent SSR benefits. The one-year marriage duration requirement mentioned above offsets this incentive. Besides, the starting age is 62 for the first claim of SSR payment. Why people have to instantaneously get married at precisely 65? In conclusion, SSR benefits should not be majorly responsible for a divorce discontinuity at 65. Though the income effect of SSR benefit might have a continuous impact.

2.3 Econometric Method

Age is the most important factor to determine whether an individual qualifies for Medicare coverage, other insurance plans supplement to Medicare, and Medicare-Medicaid dual-eligibility. My identification strategy relies on age as an exogenous assignment variable. Those who are just above the 65-year-old threshold are assigned the eligibility for these Medicare related benefits. Following standard settings of regression discontinuity design (RDD) (see Lee and Lemieux (2010)), it is assumed that the counterfactual divorce behavior is continuous in age at 65, if the eligibility for these public health insurance benefits never expands at 65 (or expanded all the time). In the context of this paper, the discontinuity in divorce rate at 65 potentially reflects the amount of Medicaid divorce which were avoided due to the exogenous occurrence of these insurance benefits.

Formally, the regression model is written as:

$$y_i = \alpha + \theta \cdot 1(age_i \geq 65) + \sum_{k=1}^{p} \beta_{1k} \cdot age_i^k + \sum_{k=1}^{p} \beta_{2k} \cdot age_i^k \cdot 1(age_i \geq 65) + X_i\gamma + \varepsilon_i \tag{2.1}$$

y_i is the outcome variable, indicator of divorce. age_i is the assignment variable, $1(age_i \geq 65)$ is the cutoff variable (an indicator equals 1 if the assignment variable exceeds the 65-threshold, equals zero otherwise). X_i are a set of covariate controls. ε_i is a mean zero regression error term. Since age_i is a discrete variable, nonparametric identification is infeasible in this case. I use p-order polynomial of age_i, fully interacted with the cutoff variable, to approximate the true continuous function. With good enough statistical performance evaluated by certain goodness-of-fit tests, such as Lee-Card test and AIC statistic, the optimal polynomial order p is chosen (see Lee and Lemieux (2010), Lee and Card (2009)). Lee and Card (2009) also suggests to use robust standard error clustered at age to adjust for potential parametric misspecification error.

Following the tradition of empirical papers that implement RDD, the assignment variable age_i is normalized by subtracting 65 form the real age (in years). That is, $age_i = 0$ if individual i is 65, $age_i = 1$ if individual i is 66, and $age_i = -1$ if individual i is 64, etc. Therefore, in the baseline regression model which excludes controls variables X_i, the intercept α captures the predicted conuterfactual divorce rate (as a benchmark level) at 65. I report the intercept estimate from the control-free baseline models. When control variables are included in the regression, the meaning of the intercept is ambiguous hence it is not reported.

The reduced-form parameter θ is our parameter of interest. It captures the discontinuity of divorce rate at 65, which might reflect the existence of a divorce gap and potentially measures the reduction of Medicaid divorce (as an impact) due to the occurrence of Medicare at 65 . By comparing the RD estimate θ with the intercept α, we can draw conclusion on the relative change (change in percent) of the divorce rate.

Social Security Retirement (SSR) benefit by its claiming rules should not have discontinuous effect on divorce behavior at 65. But the income effect of SSR payment might have a continuous impact. I will also run RD regressions of Social Security Income to test its continuity. Besides, in order to control for the continuous income effect, I add Social Security Income into the regression as a control variable. Other control variables include year effect, state effect, gender, race, and education level.

2.4 Data

2008-2015 American Community Survey (ACS) is the major data source in this paper. ACS is an annual interview survey which records 1% national representative random sample each year. The pooled ACS data set documents almost six million observations and collects rich information about the interviewees such as their marital status, health insurance status, geographic identifiers, and a large number of other demographic and economic variables. In regression analysis, our full sample is restricted to individuals aged between 55 and 75. Age is measured in terms of years. The full sample size is 5894947. Within each age cohort cell, the number of observations range from 168377 (75-cohort) to 377064 (55-cohort). Given the large within-cell sample size, the sample divorce rate and other summary statistics by age cohort should be asymptotically quite accurate. The large number of observations also allows us to use high-order polynomial (up to 4th order) to approximate the true continuous trend of divorce rate over age. Although the number of observations is clearly decreasing as age increases, mortality should not confound my result as long as mortality does not discontinuously jump at age 65.

Table 2.1 presents summary statistics of 62-67 cohorts. Notice that health insurance coverage rate increases dramatically at age 65. There is also obvious decrease in divorce rate at 65. The comprehensive analysis result are presented in Section 5.

Heterogeneous effect might exist across different subgroups. In order to identify heterogeneous effects, I stratify the full sample into subsample based on gender, race, and education level. Besides, as mentioned in Section 2.4, in Alabama, Arizona, Connecticut, Delaware, DC, Mississippi, New York, and Vermont, there are no asset tests for participating in Medicare Savings Programs. Thus I also stratify the sample based on whether the observed individuals resided in these no-limit states or in states that impose asset limit. To examine whether ACA and Medicaid expansion had significant impact to reduce Medicaid divorce, I split the sample into subsamples which respectively cover individuals in pre-ACA period (2008-2013), post-ACA period (2014-2015) in expanded states, and post-ACA period in non-expanded states.

2.5 Results

2.5.1 Baseline Results and Robustness Checks

In RDD regression analysis, choice of polynomial order is a critical issue. Suggested by Lee and Lemieux (2010), I select the optimal polynomial order based on Lee-Card Test statistic and AIC statistic. Table 2.2 presents the RD coefficient estimates in divorce rate at 65 from various polynomial specifications. In both of first, second, and third order polynomial regression, the Lee-Card Tests all reject the null hypothesis at 0.1 significance level. In fourth order polynomial regression, the null hypothesis is not rejected by the Lee-Card Test. Besides, the fourth order polynomial regression has the smallest AIC statistic. Therefore, fourth order polynomial is chosen and considered optimal.

In fact, the RD estimates are all significant and negative regardless of the polynomial order, indicating that the divorce gap does exist in the full sample and the result is robust. According to the optimal fourth order regression, the predicted counterfactual divorce rate is 17.22 percentage points in 65-cohorts. But the divorce rate discretely drops by 0.709 percentage points, which accounts for a 4.1 percent decrease.

I also follow Lee and Lemieux (2010) and calculate the robust standard error clustered at age. Table 2.3 Column (2) reports the result. The significance of the RD estimate is not affected. I also include demographic controls and SSI controls into the regression model. Both the point estimate and the clustered standard error do not change a lot, as shown in Column (3) and (4). The point estimate is -0.678 in the full model in column (4).

Then I vary the RD bandwidth from 2 years to 5 years. Table 2.4 shows that all estimates are robustly and significantly negative.

Figure 2.3 presents the graphical illustration of the discontinuity in Medicare coverage rate and Medicaid coverage rate at 65. Table 2.5 reports the RD estimates. The proportion of population being covered by Medicare discretely increased by 63.57 percentage points at 65. The Medicaid coverage rate also jumped by 1.97 percentage points, which accounts for a 19.4 percent increase. As a consequence, the overall insured rate also discontinuously increased by 8.28 percentage points.

Table 2.6 presents the RD estimates in Social Security Income, retirement income, personal total income, wage income, employment rate, and weekly working hours. None of these estimates are significant. Figure 2.4 shows the continuity of these variables. It strongly suggests that the divorce gap at 65 is not caused by these potential confounders. As already clarified above, the rules of claiming Social Security Retirement (SSR) spouse dependent benefit or ex-spouse dependent benefit neither discourage divorce at 65 nor encourage immediate remarriage at 65. The RD estimates and the pictures indicate that the average amount of Social Security Income is also continuous at 65. In the context of RDD, the income effect of SSI on divorce is at most continuous. Thus I control for these continuous income effect by adding SSI as a control covariate into the regression model.

2.5.2 Divorce Gap Heterogeneity

The divorce gap varies across subpopulation. Splitting the full sample by gender, the RD estimate is -0.250 for men and -0.967 for women, as presented in Table 2.7. The divorce gap for men is statistically insignificant, while the women experienced a 4.94 percent significant decrease in divorce. Adding controls has little impact on the significance and magnitude of the RD estimate. The gender difference of the divorce gap might suggest that Medicaid divorce is more prevailing when the sick spouse is female. This result parallels with the descriptive analysis of Karraker and Latham (2015), which finds that the wife's illness onset are more likely to incur divorce, while such association did not exist when the husband got sick.

Huge heterogeneity also exists by race. The RD estimate is insignificant for white people. However, for black people, the point estimate of the divorce gap is as large as -1.427 percentage points. which accounts for a 6.11 percent decrease. The point estimate is about twice of the full-sample estimate. The divorce gap is significant for Asians but insignificant for Hispanics.

Surprisingly, the heterogeneity by education level seems minimum. For those seniors without a college degree, the point estimate of divorce gap is -0.752. For college educated people, the estimate is -0.643. They are both significantly nonzero but statistically indistinguishable from each other.

2.5.3 Discussion: Asset Test

The main purpose for Medicaid divorce is to help the sick spouse to pass the asset test for public health insurance program eligibility. Since the divorce gap at age 65 measures the discrete reduction in Medicaid divorce, the magnitude of the divorce gap should be associated with states' settings of the asset test.

Here I consider two scenarios: Medicare savings programs and 2014 ACA Medicaid expansion. First, for a couple aged over 65, it is more likely to get coverage by Medicare savings program if they reside in states that do not impose asset limit for their Medicare savings programs, rather than in states that do impose. Thus in states with asset limit, the incentive for a post-65 Medicaid divorce should be smaller, which drags down the divorce rate among post-65 cohorts. As a consequence, we should see a larger divorce gap in these states.

Second, in states expanded Medicaid after 2014, adults aged below 65 can qualify for Medicaid coverage as long as they earn an income below 133% FPL, regardless of their asset levels and categories. The cancellation of the asset test reduced the prevalence of divorce among 50-64 cohorts in expanded states (see Slusky and Ginther (2017)). Since the divorce rate was dragged down for pre-65 cohorts, we should see a smaller or even insignificant divorce gap in expanded states after 2014.

As expected, whether states have asset test for Medicare Savings Program plays an important role in the post-65 reduction of Medicaid divorce. The RD estimates across states are reported in Table 2.10. In states that does not impose asset test for participating in post-65 Medicare Savings Programs, the divorce gap estimate is as large as -1.122 percentage points. In states do have an asset limit, the divorce gap estimate is only -0.498. Both the estimates are significantly nonzero. And two estimates are also significantly different from each other. The difference between the divorce gap is graphically obvious, as seen in Figure 2.8. It suggests that the absence of asset tests in these no-limit states is one of the key drivers to reduce Medicaid divorce.

Table 2.11 presents the estimates by ACA period and Medicaid expansion states. Prior to 2014, the divorce gap estimate is -0.749 percentage points, which accounts for a 4.39 percent decrease. The divorce gap estimate is -0.570 in non-expanded state after 2014. Although it is slightly smaller than the pre-ACA divorce gap, it is still significant and these two estimates are statistically indistinguishable. Not surprisingly, the divorce gap estimate is insignificant in those post-ACA expanded states. Although the point estimate is actually of considerable scale, but the standard error is almost identical to the point estimate. As a consequence, the t-statistic is not large enough to reject the nonzero null hypothesis. The absence of evidence for divorce gap in post-ACA expanded states suggestively indicates that Medicaid divorce is reduced due to the asset test cancellation and enhanced income limit.

Separated couples are still legally married. Separation do not influence the asset level of the sick spouse. I find no evidence of “separation gap" at the 65-threshold, as indicated in Table 2.12.

2.6 Conclusion

In this paper I address the question about how age-based public health insurance eligibility can possibly affect divorce behavior and family structure. Once an individual reaches 65, he/she can access uniform and affordable Original Medicare coverage. Besides, seniors are offered a menu of Medigap policies, Medicare Advantage plans, Medicare savings programs, and Medicaid-Medicare dual eligibility, which further reduce and cap the out-of-pocket expense on health care. These public health insurance benefits shield the risk of spend down hence offset the incentive and necessity for Medicaid divorce. Based on this idea, my empirical analysis finds the divorce rate decreased by about 0.7 percentage points at 65 in the entire United States during 2008-2015.

My heterogeneity analysis suggests that Medicaid divorce is more prevalent for black couples. Also, if the female spouse is the sick spouse, a Medicaid divorce would be more likely to happen.

This study has several policy implications. As many studies have pointed out, the rules of Medicaid eligibility for couples is flawed (see Miller (2015)). The restrictive financial requirement (especially the asset test) is the main reason to cause Medicaid divorce. Although Medicaid divorce is, to some extent, “fake" divorce, it undoubtedly incurs welfare loss [4]. A revised system of eligibility rules which relax the restriction for the healthy spouse is called for. Policies like Affordable Care Act and Medicaid expansion which aim at expanding the provision of low-cost health insurance plans and expanding the coverage range of public health insurance might significantly improve the marriage welfare of nearly elderly couples.

[4] Kristof, Nicholas. “Until Medical Bills Do Us Part," *The New York Times*, Aug 29, 2009

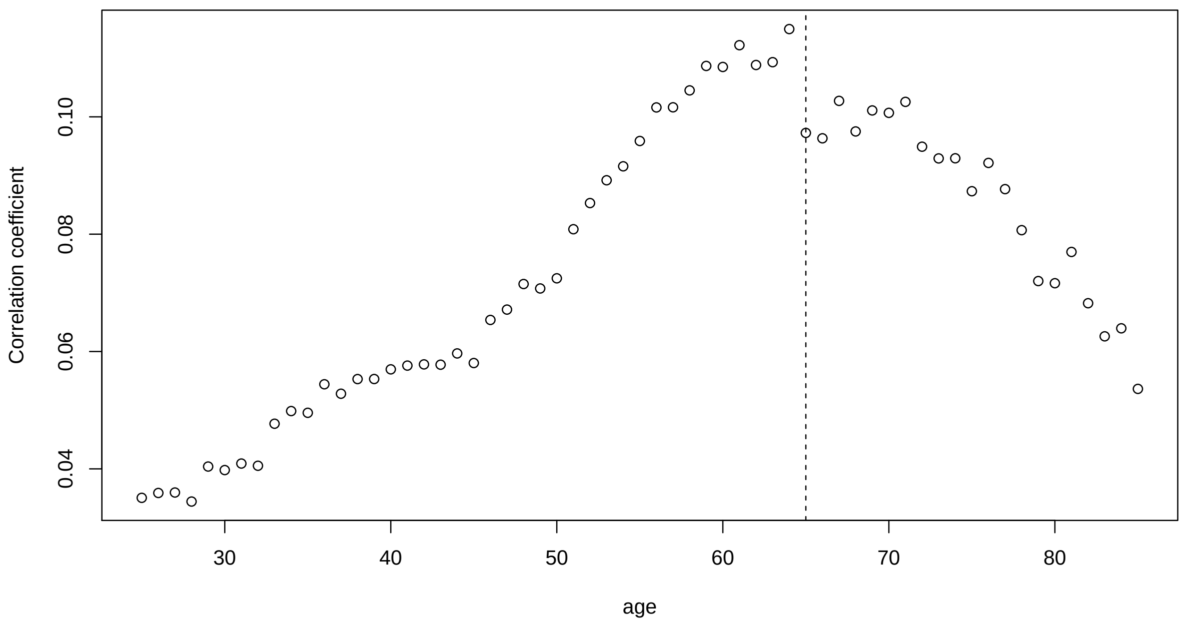


Figure 2.1: Correlation Coefficient between Being Divorced and Being Covered by Medicaid, from 25-cohort to 85-cohort

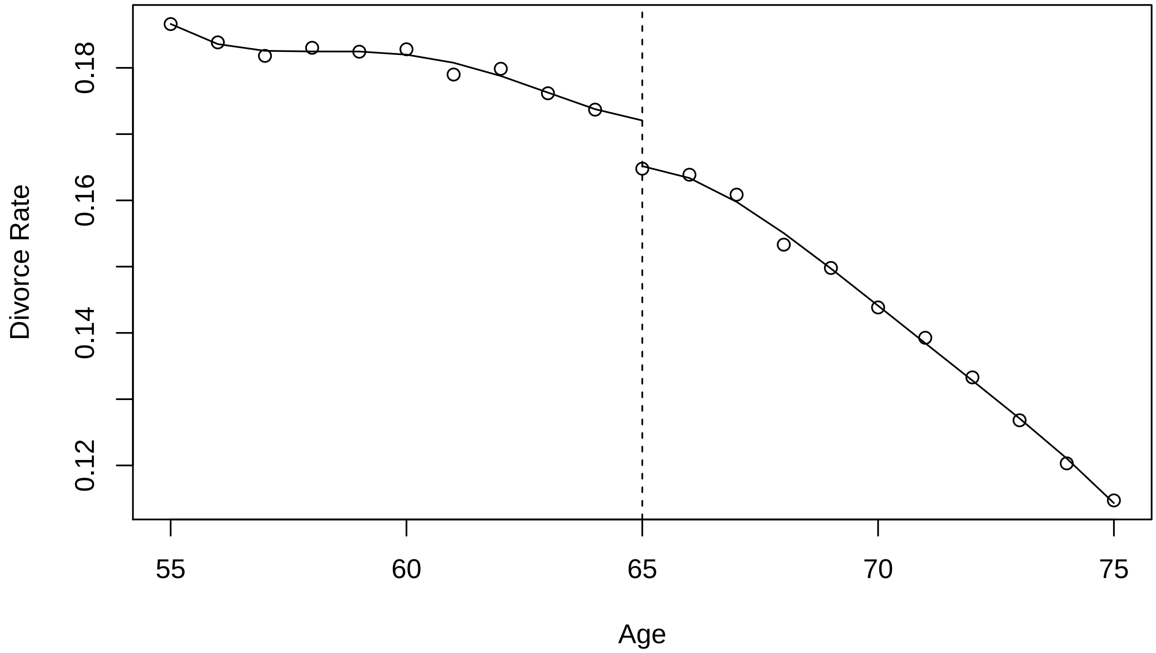


Figure 2.2: Regression Discontinuity in Divorce Rate at 65

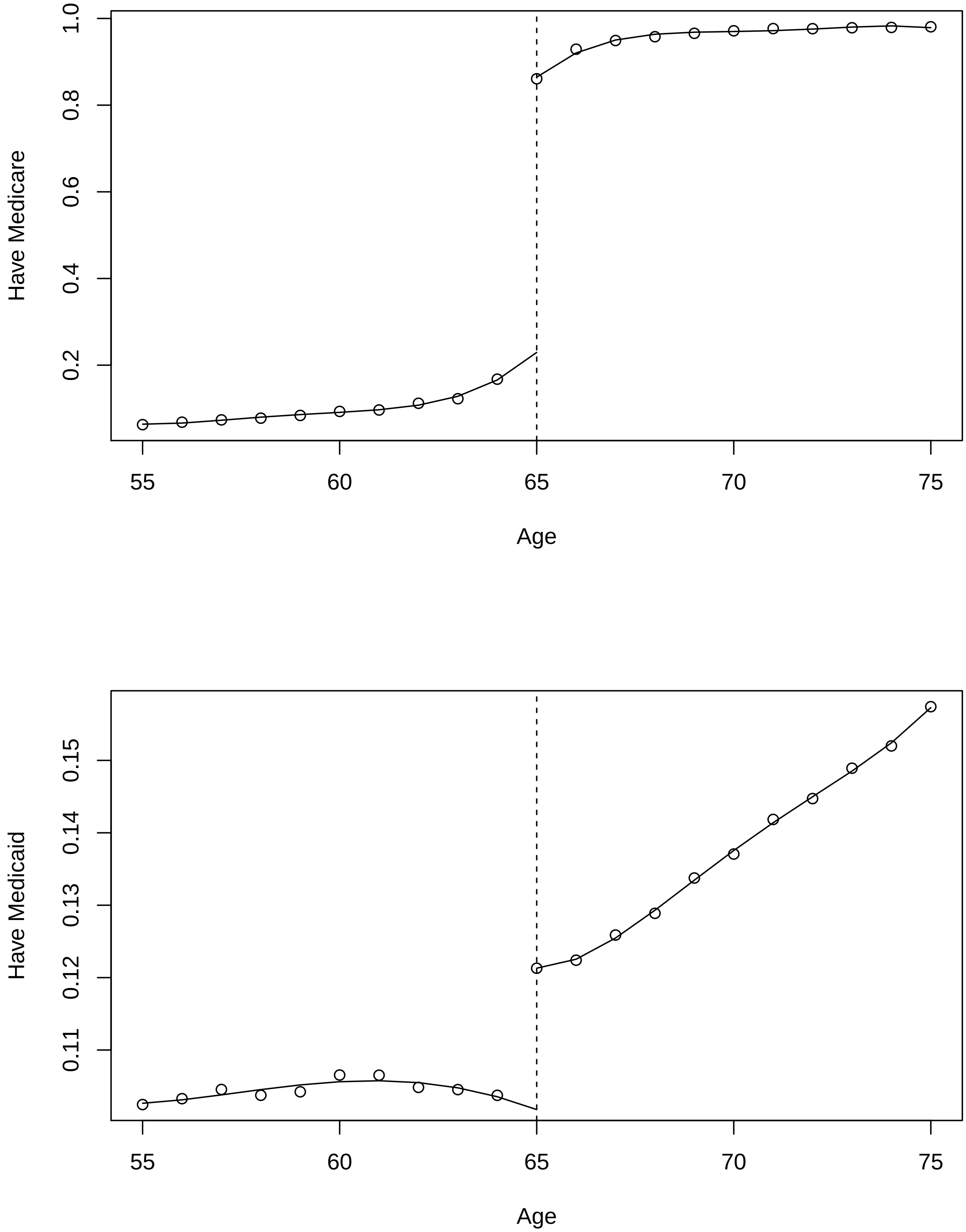


Figure 2.3: Regression Discontinuity in Medicare Coverage Rate and Medicaid Coverage Rate at 65

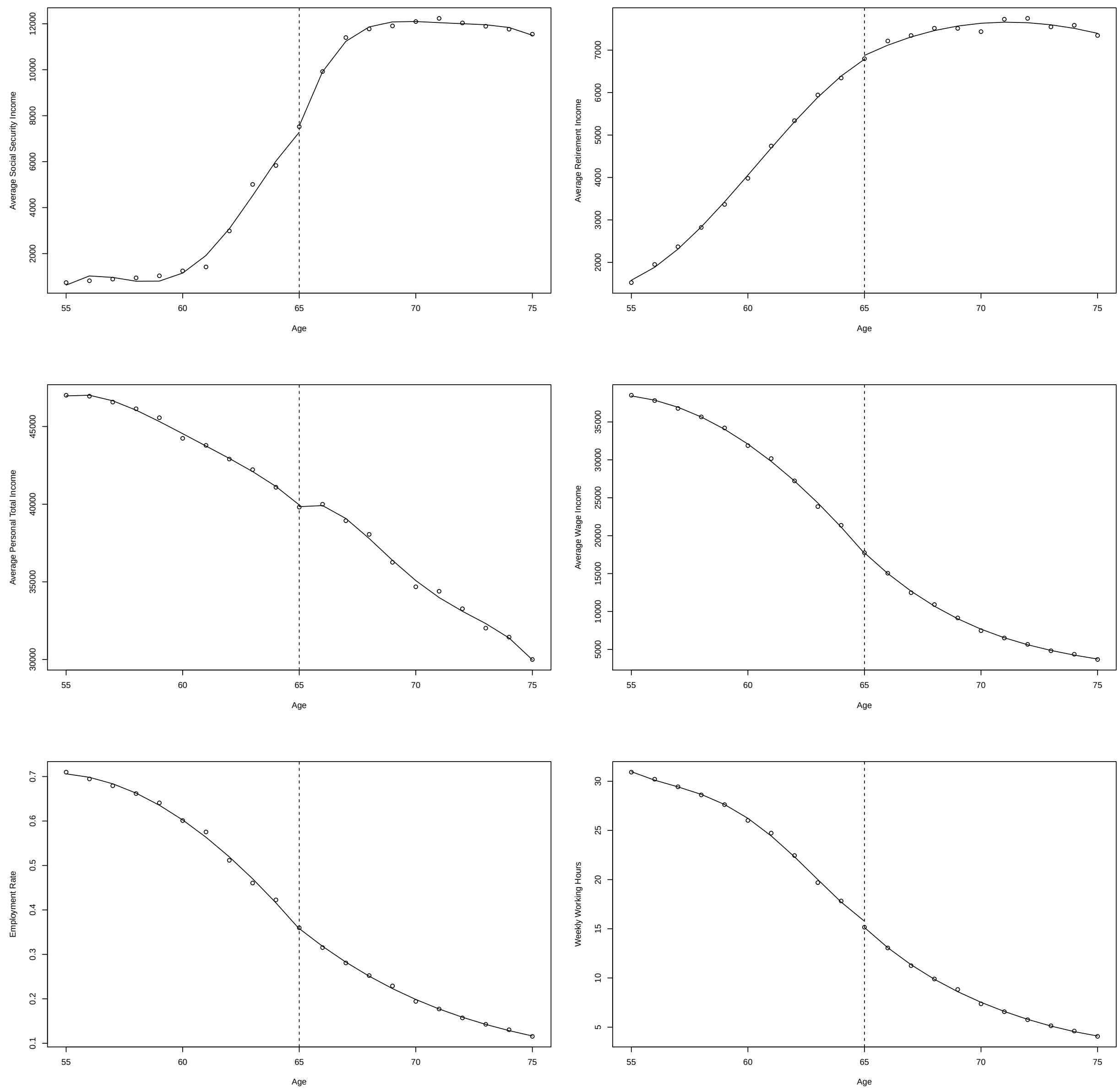


Figure 2.4: Regression Discontinuity in Potential Confounders at 65

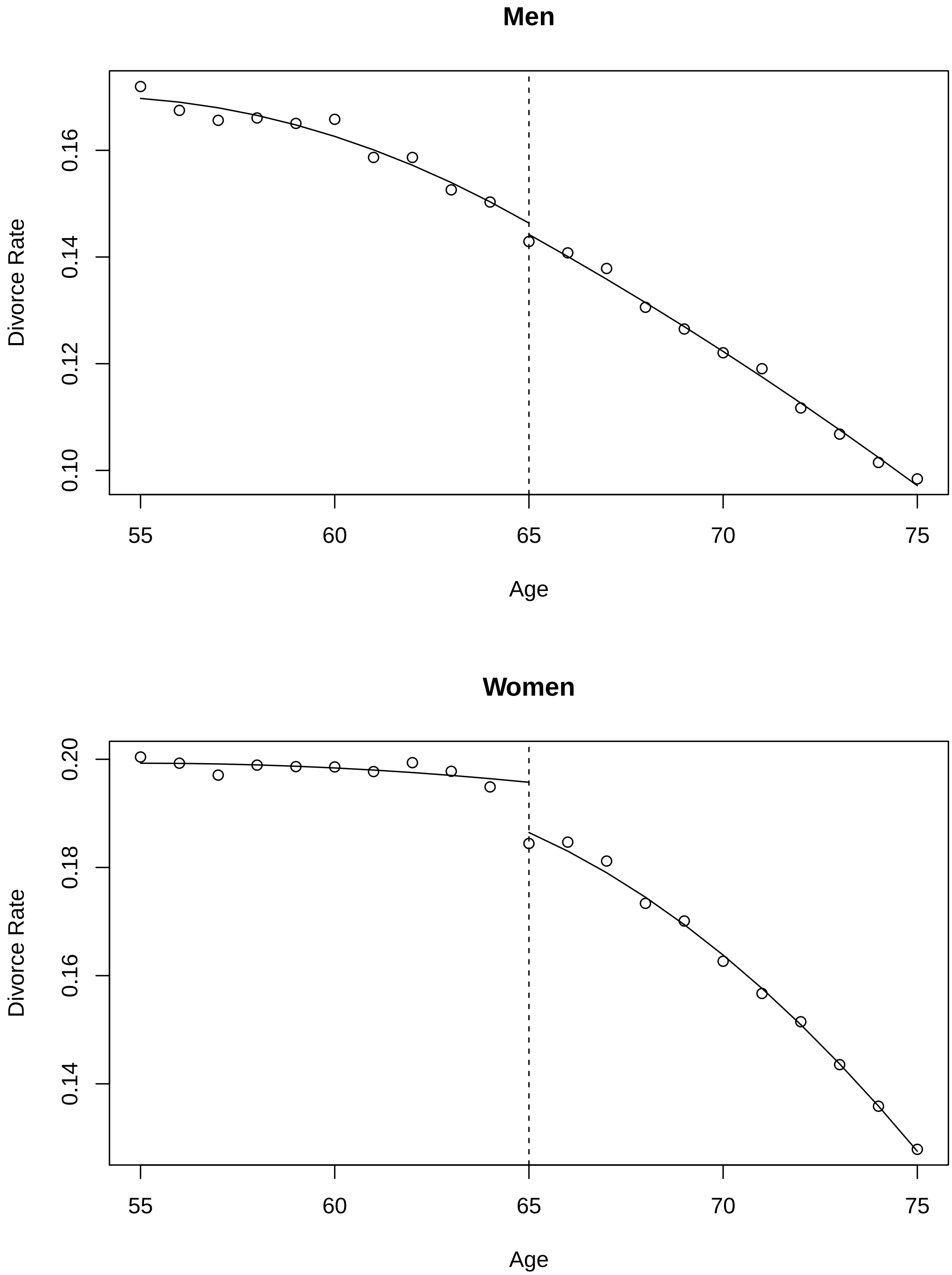


Figure 2.5: Regression Discontinuity in Divorce Rate at 65, by Gender

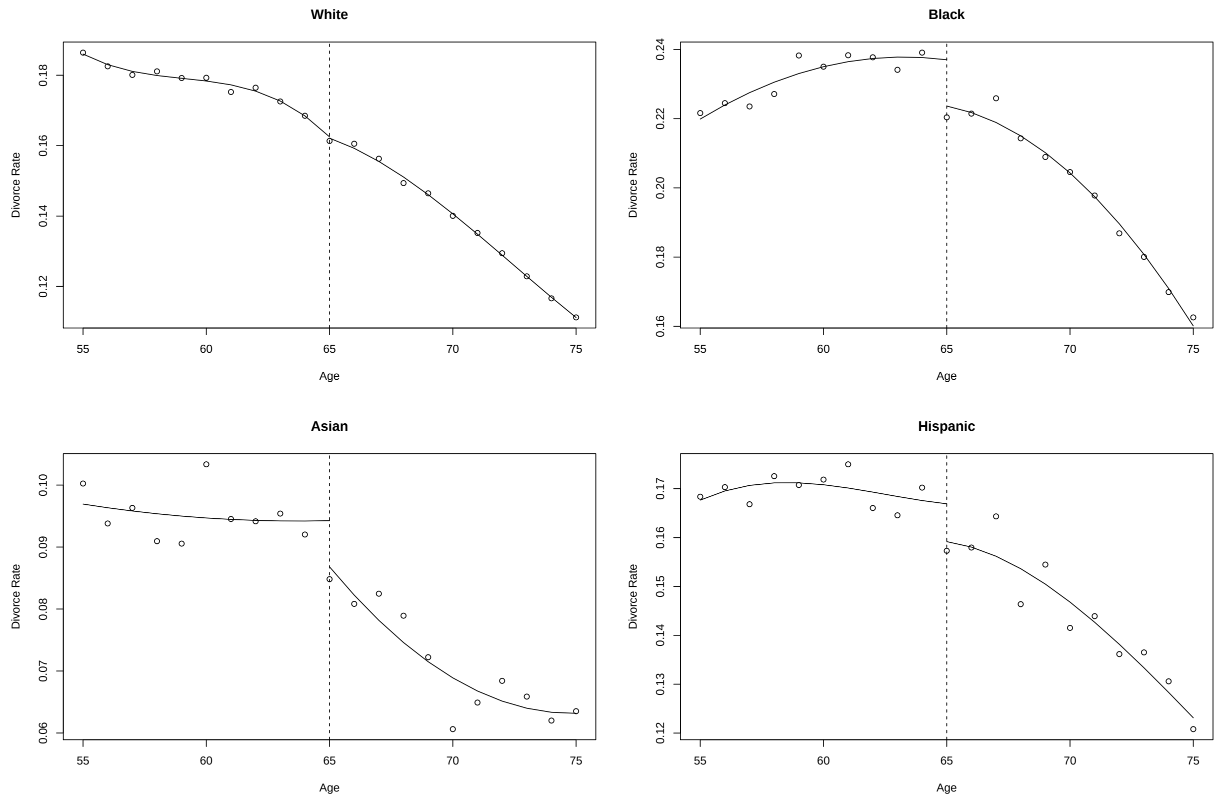


Figure 2.6: Regression Discontinuity in Divorce Rate at 65, by Race

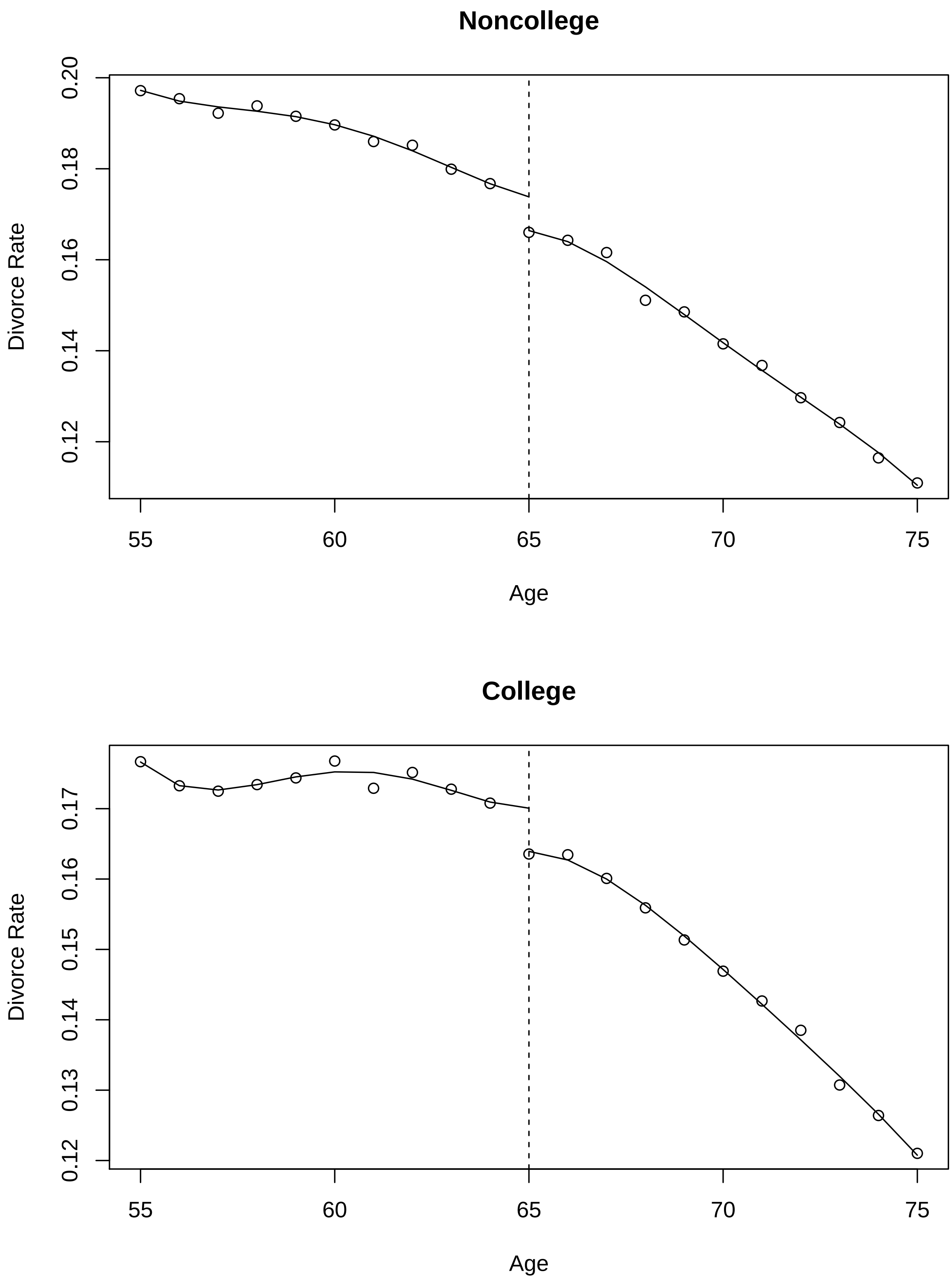
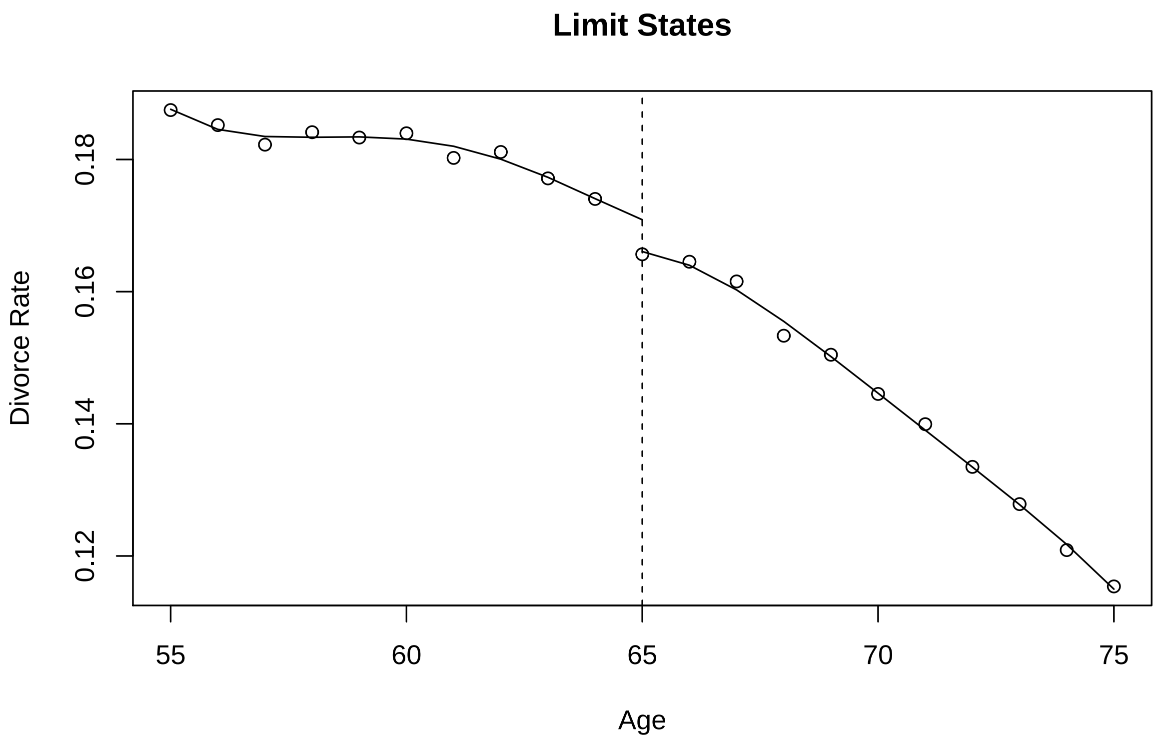


Figure 2.7: Regression Discontinuity in Divorce Rate at 65, by Education



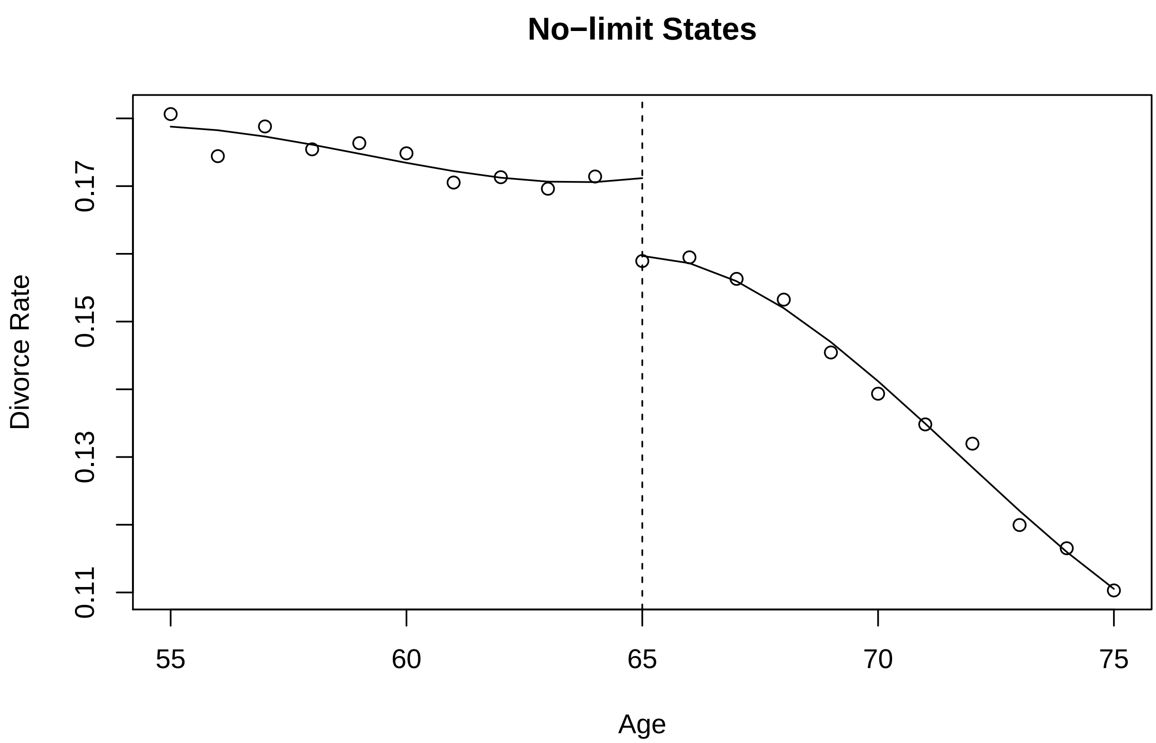


Figure 2.8: Regression Discontinuity in Divorce Rate at 65, by Whether States Impose Asset Limit

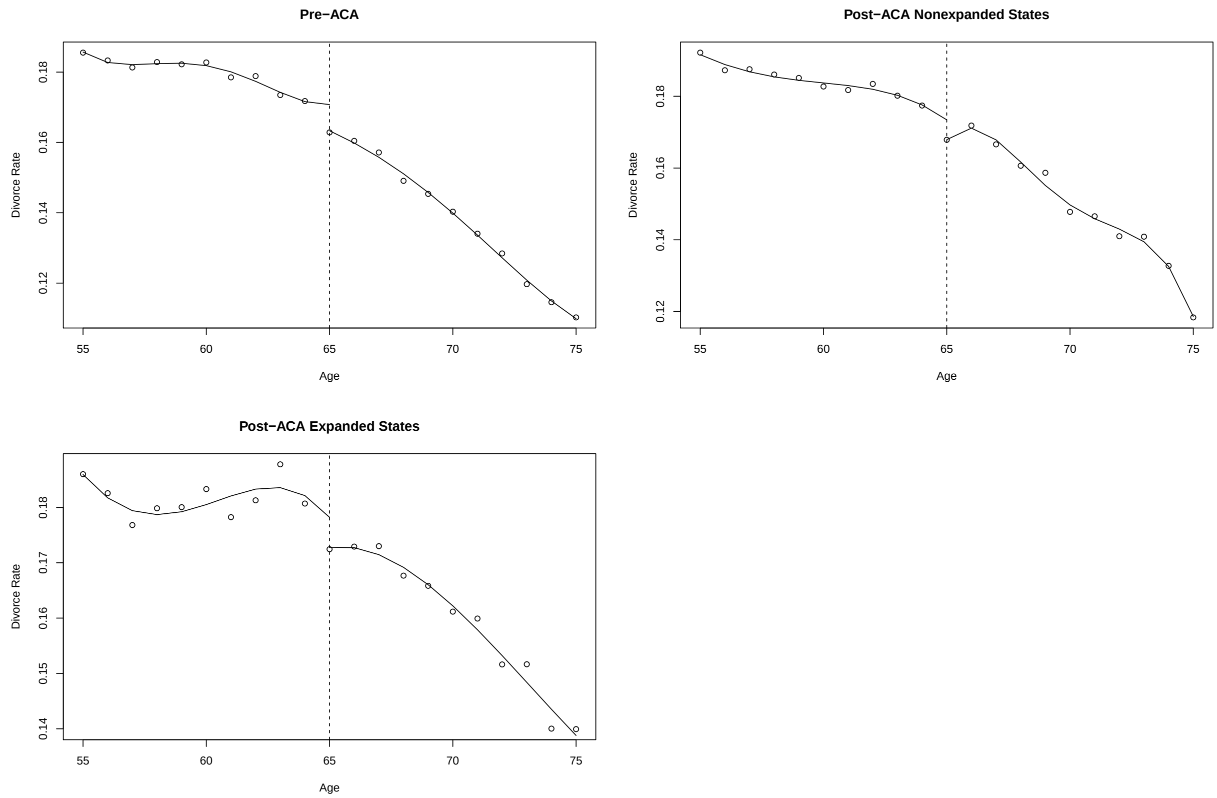


Figure 2.9: Regression Discontinuity in Divorce Rate at 65, by ACA and Medicaid Expansion

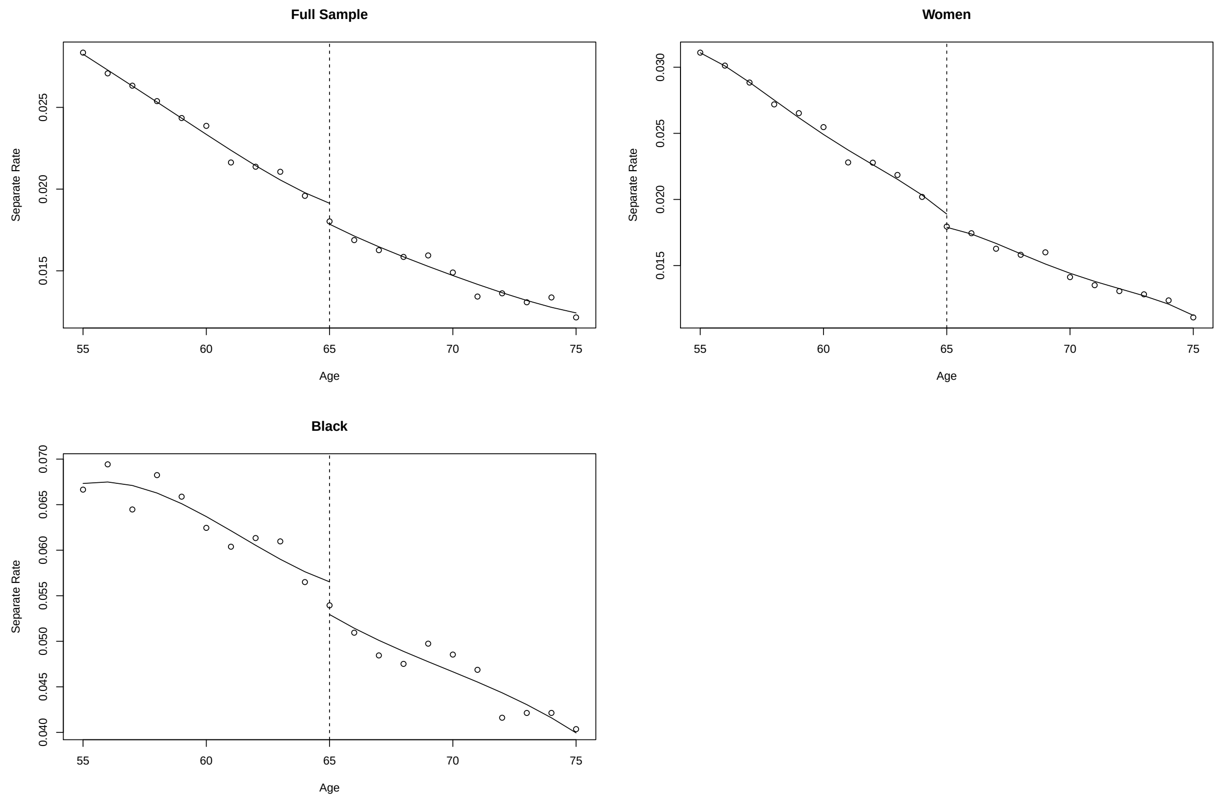


Figure 2.10: Regression Discontinuity in Separation Rate at 65

Table 2.1: Summary Statistics of Age 62-67 Cohorts

	Age					
	62	63	64	65	66	67
# Observations	326836	311471	300366	296878	277405	262717
Divorce Rate	17.99	17.62	17.37	16.48	16.39	16.09
Health Insurance:						
Insured Rate	89.17	89.30	89.62	97.87	98.59	98.72
Medicare Coverage	11.21	12.26	16.77	86.09	92.91	94.92
Medicaid Coverage	10.48	10.45	10.37	12.13	12.24	12.59
Demographic Covariates:						
Female	52.07	52.18	52.46	52.69	52.60	53.12
White	81.08	81.58	81.83	82.02	82.94	83.17
Black	10.40	10.20	10.02	9.83	9.39	9.31
College	52.93	52.36	51.18	49.98	49.29	47.85
Employment and Income Covariates:						
Employed	51.15	46.04	42.26	35.97	31.53	28.07
Weekly Work Hours	22.45	19.69	17.83	15.16	13.05	11.25
Wage Income	27226	23838	21377	17744	15049	12478
Retirement Income	5338	5943	6344	6798	7216	7345
Personal Total Income	42906	42223	41089	39809	39998	38936
Social Security Income	2895	5009	5833	7523	9922	11399

Data source: American Community Survey 2008-2015 data.

Table 2.2: Discontinuity Estimates in Divorce Rate at Age 65, with Different Polynomial Order Specifications

	Full Sample			
	Dependent variable: Indicator for divorce			
	(1)	(2)	(3)	(4)
Age $\geq$ 65 cutoff	-0.608^{***}	-0.624^{***}	-0.249^{*}	-0.709^{***}
	(0.061)	(0.095)	(0.143)	(0.228)
Intercept	17.470^{***}	17.251^{***}	16.801^{***}	17.217^{***}
	(0.045)	(0.078)	(0.129)	(0.218)
Polynomial Order	1	2	3	4
Lee-Card Test	0.000	0.003	0.081	0.162
AIC	14585755	14585702	14585680	14585675
N	5894947	5894947	5894947	5894947

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. OLS standard errors are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.3: Discontinuity Estimates in Divorce Rate at Age 65

	Full Sample			
	Dependent variable: Indicator for divorce			
	(1)	(2)	(3)	(4)
Age $\geq$ 65 cutoff	-0.709^{***}	-0.709^{***}	-0.673^{***}	-0.678^{***}
	(0.228)	(0.185)	(0.185)	(0.185)
Intercept	17.217^{***}	17.217^{***}		
	(0.218)	(0.182)		
Clustered SE	No	Yes	Yes	Yes
Demographic Controls	No	No	Yes	Yes
SSI Control	No	No	No	Yes
N	5894947	5894947	5894947	5894947

The estimates are reported in terms of percentage points. The basic model includes quartic polynomial of age, fully interacted with indicator $1(age \geq 65)$. Demographic control variables include indicators for year, state, gender, race, and education. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Standard errors are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.4: Discontinuity Estimates in Divorce Rate at Age 65, with Different Bandwith Specifications

	Dependent variable: Indicator for divorce							
Age range:	63 - 67		62 - 68		61 - 69		60 - 70	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Age $\geq$ 65 cutoff	-0.611^{***}	-0.587^{***}	-0.421^{**}	-0.402^{**}	-0.587^{***}	-0.578^{***}	-0.508^{***}	-0.514^{**}
	(0.039)	(0.056)	(0.133)	(0.145)	(0.160)	(0.168)	(0.159)	(0.166)
Intercept	17.122^{***}		17.039^{***}		17.236^{***}		17.202^{***}	
	(0.000)		(0.037)		(0.086)		(0.054)	
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
N	1448837	1448837	2022191	2022191	2586022	2586022	3161120	3161120

The estimates are reported in terms of percentage points. The models include a linear term of age, fully interacted with indicator $1(age \geq 65)$. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.5: Discontinuity Estimates in Insurance Coverage at Age 65

	Full Sample		
Dependent variable:	Medicare Coverage	Medicaid Coverage	Any Insurance Coverage
	(1)	(2)	(3)
Age $\geq$ 65 cutoff	63.572***	1.971***	8.283***
	(0.980)	(0.157)	(0.290)
Intercept	22.820***	10.155***	89.630***
	(0.922)	(0.157)	(0.285)
Clustered SE	Yes	Yes	Yes
Controls	No	No	No
N	5894947	5894947	5894947

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.6: Discontinuity Estimates in Potentially Confounding Covariates at Age 65

	Full Sample					
Dependent variable:	Social Security Income	Retirement Income	Total Income	Wage Income	Employed	Weekly Working Hours
	(1)	(2)	(3)	(4)	(5)	(6)
Age $\geq$ 65 cutoff	110	44	-537	103	0.002	-0.65
	(756)	(104)	(360)	(525)	(0.015)	(0.45)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	5894947	5894947	5894947	5894947	5894947	5894947

The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. Control variables include year effect, state effect, gender, race, and education. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.7: Discontinuity Estimates in Divorce Rate at Age 65, by Gender

	Dependent variable: Indicator for divorce			
	Men		Women	
	(1)	(2)	(3)	(4)
Age $\geq$ 65 cutoff	-0.250	-0.197	-0.967^{***}	-1.063^{***}
	(0.164)	(0.191)	(0.217)	(0.193)
Intercept	14.656^{***}		19.596^{***}	
	(0.138)		(0.165)	
Clustered SE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	2788260	2788260	3106687	3106687

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. Control variables include year effect, state effect, gender, race, education, and Social Security Income. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.8: Discontinuity Estimates in Divorce Rate at Age 65, by Race

	Dependent variable: Indicator for divorce							
	White		Black		Asian		Hispanic	
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age $\geq$ 65 cutoff	-0.036	0.062	-1.427^{***}	-1.493^{***}	-0.829^{**}	-0.912^{**}	-0.720	-0.422
	(0.164)	(0.164)	(0.375)	(0.360)	(0.388)	(0.367)	(0.619)	(0.624)
Intercept	16.243^{***}		23.374^{***}		9.476^{***}		16.586^{***}	
	(0.146)		(0.306)		(0.353)		(0.602)	
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
N	4916158	4916158	539317	539317	214664	214664	426896	426896

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. Control variables include year effect, state effect, gender, race, education, and Social Security Income. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.9: Discontinuity Estimates in Divorce Rate at Age 65, by Education

	Dependent variable: Indicator for divorce			
	Noncollege		College	
	(9)	(10)	(11)	(12)
Age $\geq$ 65 cutoff	-0.752^{***}	-0.723^{***}	-0.643^{***}	-0.601^{***}
	(0.202)	(0.205)	(0.197)	(0.179)
Intercept	17.386^{***}		17.025^{***}	
	(0.197)		(0.195)	
Clustered SE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	3006951	3006951	2887996	2887996

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. Control variables include year effect, state effect, gender, race, education, and Social Security Income. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.10: Discontinuity Estimates in Divorce Rate at Age 65, by Whether States Sets Up MSP Asset Limit

	Dependent variable: Indicator for divorce			
	With-Limit States		No-Limit States	
	(1)	(2)	(3)	(4)
Age $\geq$ 65 cutoff	-0.498^{**}	-0.468^{**}	-1.122^{***}	-1.029^{***}
	(0.201)	(0.200)	(0.265)	(0.305)
Intercept	17.095^{***}		17.080^{***}	
	(0.197)		(0.256)	
Clustered SE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
N	5140290	5140290	754657	754657

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. Control variables include year effect, state effect, gender, race, education, and Social Security Income. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.11: Discontinuity Estimates in Divorce Rate at Age 65, by ACA Period and Medicaid Expansion States

	Dependent variable: Indicator for divorce					
	Pre-ACA		Post-ACA Nonexpanded		Post-ACA Expanded	
	(1)	(2)	(3)	(4)	(5)	(6)
Age $\geq$ 65 cutoff	-0.749^{***}	-0.679^{**}	-0.570^{*}	-0.633^{**}	-0.631	-0.760
	(0.241)	(0.251)	(0.276)	(0.250)	(0.634)	(0.565)
Intercept	17.070^{***}		17.369^{***}		17.897^{***}	
	(0.237)		(0.274)		(0.633)	
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes
N	4285358	4285358	962974	962974	646615	646615

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. Control variables include year effect, state effect, gender, race, education, and Social Security Income. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Table 2.12: Discontinuity Estimates in Separation Rate at Age 65

	Dependent variable: Indicator for separation		
	Full Sample	Women	Black
	(1)	(2)	(3)
Age $\geq$ 65 cutoff	-0.094	-0.047	-0.349
	(0.068)	(0.076)	(0.309)
Clustered SE	Yes	Yes	Yes
Controls	Yes	Yes	Yes
N	5894947	3106687	539317

The estimates are reported in terms of percentage points. The models include polynomial of age, fully interacted with indicator $1(age \geq 65)$. The estimates are based on pooled 2008-2015 ACS data. All regressions are weighted by personal sampling weight. Robust standard errors clustered at age are reported in parentheses. (* 0.1, ** 0.05, *** 0.01)

Chapter 3

Job Polarization During Economic Expansion: 2000-2006 Housing Boom and U.S. Labor Market Occupational Composition

3.1 Introduction

Job polarization since 1980s reshaped the labor market occupational composition in the U.S. There exited relatively declining trend in employment and wages for jobs ranked in the middle by the education level of workers. On the other hand, both the employment share and wages of jobs ranked in the upper side and the lower side were relatively increasing. The "U-shape" structure of the employment change and wage change of the U.S. jobs is put on the agenda table. It does not only seize the attention from academics, but it is also influencing the recent US presidential election debate. The disappearing of middle-skill jobs—and the complaint from the people became unemployed, tend to affect the future policy making in subjects like globalization, outsourcing, international trade, and foreign immigrants.

Due to the importance of this issue, researchers in economics devote to find an explanation for the recent job polarization trend. Autor, Levy and Murnane (2003), Acemoglu and Autor (2010) stressed the task contents of occupations. For each job, there are three dimensions of tasks which require different skills of the person working in that job. Abstract tasks require people to think abstractly and conduct interpersonal communications adaptively. Routine tasks require people to stay focused on a certain set of standardized activity. Manual tasks require people to coordinate eyes, hands, and feet to deal with the inconsistently changing situations. To sum up, people working in a job position apply their skills on different tasks to produce output. There exists strong relation between people's education level and the tasks they regularly perform in their jobs. The majority of the disappearing middle-skill jobs, as mentioned above, happens to be intensive in routine tasks. Researchers argue that the technological change in recent decades is biased to the routine tasks. It's complementary to people performing abstract tasks and manual tasks. The routine workers, however, are being replaced by machine automation. Technology advancement is reducing the demand of routine intensive occupations which are ranked in the middle in terms of wages and education level. The workers used to work in these routine jobs are forced to shift toward the jobs in lower rank or in higher rank. According to the recent empirical research, a lot of evidences support that Routine Biased Technological Change (RBTC) is a powerful explanation to the job polarization in recent decades. In fact, the RBTC and the job polarization are reshaping the structure of the U.S. labor composition. The concept of division of labor by Adam Smith overspreads to the global economy. Not only in the U.S., but also in other modern industrialized countries, more higher-educated people are working on innovative activity such as STEM and art, pushing the human civilization forward. People with lower education are directed to the nontradable service sector of the local community. The old-fashion, labor-intensive routine tasks are shifted to developing countries, which have comparative advantages in labor cost.

Living in the historical era of the U.S. job polarization, researchers discovered that the decreases in the employment share of routine occupations were concentrated in the period of economic recession. Jaimovich and Siu (2014) pointed out that in the three recent business cycles, although the aggregate output recovered soon after the recession trough, the jobs were gone forever. The employment rate and participation rate did not bounce back to the pre-recession level. From the aggregate data, the economic recovery is “jobless". When we disaggregate the data by occupations, among these forever-gone jobs, over 100% of them contained intensive routine tasks in the 1982 recession. On the contrary, employment share in non-routine intensive occupations actually increased relative to the pre-recession level. Evidence shows that the job polarization phenomenon is closely related to the business cycles.

In this paper, I focus on the other side of the story: What's the pattern of the change of employment in routine occupations and non-routine occupations during the boom period? Intuitively, economic boom should create employment opportunities due to the increasing aggregate demand. More people would be filled in job positions. However, whether the routine workers would benefit from the economic expansion is not that intuitive. Further analysis needs to be conducted to give an answer. This paper aims to address this problem.

The most recent large-scale economic expansion in the U.S. was the housing boom in early 2000s. Figure 3.1 clearly shows that the housing price level experienced rapid rise starting from late 1990s. The housing price didn't drop until about 2006. Local housing boom is a measurement of local economic prosperity. The most direct effect of local housing boom on local employment opportunities is in construction sector—You have to hire people to build (Charles, Hurst and Notowidigdo (2016)). Indirectly, local housing boom might potentially increase the local demand for certain jobs through spillover effect. Purchases and buildings of houses occur in a city mainly for two reasons: (1) People living there are getting wealthy; (2) People are moving into the city. Both of the reasons are potential signals to increasing demand for jobs.

My main contribution to the literature can be summarized into three points: First, I pay my attention to the period of economic expansion. As mentioned above, local housing boom is a very good indicator for expanding labor economy. Thus I study the effect of housing boom on local employment. It is interesting to ask whether the short-term housing boom during 2000-2006 would increase the demand for certain routine intensive jobs, even though in the long run their employment shares are shrinking due to the RBTC. In the literature, most of the previous research discussed the pattern of decadal change, say, from 1980s to 2000s. And there exist few papers on connecting economic boom with job polarization.

Second, I estimate the effect of the short-term housing boom and the effect of the RBTC on the local labor market outcome at the same time. Following the spirit of Autor, Dorn and Hanson

(2015) [1] , I put the housing boom and the routine share [2] simultaneously on the right-hand side as explanatory variables.

Third, I classify all 465 3-digit occupations, which were defined in the 2000 census data, into eight groups. I make the classification based on the education level of the people in these jobs, and the degree of task intensity of the occupations. These eight occupation groups are named: high-skill local service, professor, professional, office and administrative support, others, low-skill local service, production, and construction. These occupation groups are well characterized by the nature of the jobs, the skills equipped by an average worker, the content of tasks they carry, and their average wages. These details would be covered in Section 3. In Autor and Dorn (2013), they found a dacadal pattern that in an initially highly “routine" city, low-skill labor force would transit from the routine intensive jobs to the low-skill, low-payed service sectors. While they defined the service occupation group by job titles, I define local service occupations in a much broader sense, and they are not limited to low-skill jobs. In the spirit of Moretti (2012), I pick an occupations into the local service group, if the people working in this occupation offer service directly to the local consumers, and the service is relatively non-tradable to consumers far away. By my approach, some high-skill, high-pay jobs are also included in the local service occupation group. The detailed classification of occupations enables us to perform thorough shift-share analysis. It helps us to identify the major beneficiaries in the labor market during the 2000s housing boom, and to identify the occupations to which the sacked routine workers shifted. Figure 3.3, Figure 3.4, and Figure 3.5 show the national aggregate employment shares in occupation groups.

Local labor market approach is employed in my empirical study. The degree of the housing boom, or more precisely, the magnitude of the increase in the house price level, were very different among different cities. For example, cities near the coastal areas experienced a rapid rise in housing price, while the housing market in Kansas and Texas were relatively mild. Besides, the initial labor

[1] In Autor, Dorn and Hanson (2015), the authors simultaneously estimated the effect of exposure to competition with China’s import in manufacturing, and the effect of RBTC.

[2] Routine share is a measure of the routine intensity of the local labor market employment composition. If a local labor market has a higher routine share, then it is more exposed to the RBTC, and a larger decline of demand for routine tasks is predicted. See sections below.

composition structure were also very different among cities . For example, we should expect a larger share of routine workers resided in Detroit, a typical manufacturing specialized city, than in San Francisco, which is famous for its vivid activity of IT innovation.

I exploit the cross-sectional variation of the housing boom from 2000-2006, and the cross-sectional variation of the initial labor market structure in 2000, to examine how different cities would respond to these “shocks" in terms of employment and wage in various occupations. The numerous cities and their fixed geographical locations provide us with a data set of panel structure and with relatively large sample size. The local labor market approach is proved successful in recent empirical labor market research. See Autor and Dorn (2013), Autor, Dorn and Hanson (2013), Autor, Dorn and Hanson (2015), Charles, Hurst and Notowidigdo (2016).

Through the most direct demand shock to the construction occupations, housing shock significantly increase the employment share in construction occupations. A city at the 75th percentile of housing boom experienced increase the employment share than a 25th-percentile city 6.4% more. The effect of the housing boom is widespread. Housing boom also boost the employment share in low-skill occupations such as low-skill local service, and office administrative support.

Besides, the RBTC significantly reduced the employment share in all two major routine occupation groups—office administrative support, and production. A city with 75th percentile of the routine share significantly reduced the employment share in office occupations by 2.2%, than a 25th-percentile city. The 75th-to-25th employment loss in office occupations is even larger among noncollege population. The number is as large as 4.2%.

I also implement a wage regression which exploits the rich information about individual characteristics in the micro data. I study how the wage income for individuals working in different occupations and in different locations would respond to the local housing boom and the initial local labor market employment composition.

The rest of the paper are divided into four sections. In Section 2 I introduce a simple demand-supply model to identify the one-way effect of housing boom on local labor market outcome. An instrumental variable empirical approach is stimulated by this framework. In Section 3 I present the source of the data, how I proxy the variables with data in the empirical settings, and the method of measuring and constructing the variables with data. In Section 4 I present the main empirical result of this paper. In the end, Section 5 concludes.

3.2 Empirical Approach

3.2.1 Employment Regression

In my empirical analysis, a Metropolitan Statistical Area (MSA) is the a unit of local labor market. MSAs are defined by the Office of Management and Budget (OMB). An MSA is a geographical region where high population density and economic activities are concentrated. It's assumed that the workers in an MSA can shift between jobs and sectors without moving out of the MSA, so it's very suitable unit of measurement of local labor markets. The shortcoming for MSAs is that they don't cover the whole area of the US. Many rural locations with low population density is not included in any MSAs. Therefore, the analysis in this paper is only on urban areas.

In order to estimate the causal effect of the local housing boom on the local labor market outcome, the starting point is to untangle the demand-side effect and supply-side effect. Local housing boom is a proxy of local economic prosperity, hence it creates employment opportunity. This would be reflected in the local labor market outcome.

On the other hand, the local labor market outcome would have certain impact on both local housing demand and supply. If more people are employed, or more immigrants from other places flow in, then they need a place of residence. What's more, the increase of people working in certain sectors such as construction, mortgage finance, and housing agency, would directly affect the housing construction and sales activity.

In summary, housing boom as a labor demand shock, would affect the local labor market outcome. Reversely, change in local labor market employment would stimulate local housing price level through both housing demand channel and housing supply channel. The ideas above can be written as two simultaneous equations:

$$\triangle L_j = \beta_0 + \beta_1 \triangle H_j + \beta_2 \triangle L_j^{DO} + \beta_3 \triangle L_i^S + \varepsilon_j \tag{3.1}$$

$$\triangle H_j = \alpha_1 \triangle L_j + f(\theta_j, \triangle H^{ND}) + e_j \tag{3.2}$$

First, let's look at Equation (1). In MSA j, the local labor market outcome, $\triangle L_j$, is jointly determined by the local labor demand shock and the local labor supply shock. In my paper, the local economic prosperity brought by the housing boom is a major source of the labor demand shock. Thus a measure of local housing boom, $\triangle H_j$, plays a role in the right-hand side. The rest of the demand shock is captured by the variable $\triangle L_j^{DO}$, the labor demand shock from other sectors. I leave the labor supply shock $\triangle L_j^S$ unobserved in my analysis. Also, some other unobserved mean zero disturbance, ε_j, might affect the labor market outcome.

Empirically, I use the log change of MSA-level Housing Price Index (HPI) to proxy the local housing boom labor demand shock $\triangle H_j$.

$$\triangle H_j = log(HPI_{j,2006}) - log(HPI_{j,2000})$$

Routine Biased Technological Change (RBTC) is also a labor demand shock. Stem from Autor and Dorn (2013), routine share RSH_j has become a popular empirical measurement to study job polarization. Routine share is the ratio of labor supply in well-defined [3] routine occupations to the total labor supply, in MSA j. Autor and Dorn's theoretical model predicts that if initially a city more intensively had its labor force employed in routine occupations, then in that city more employment share will be shifted from routine occupations to non-routine job positions, due to the declining demand for routine tasks caused by RBTC.

In standard spatial equilibrium models in urban economics (Roback (1982), Moretti (2011)), the growth of employment level and immigrant inflow in a city will raise the housing demand in that city. Therefore, the local labor market outcome might reversely boost the local housing boom,

[3] The precise definition of routine share is left in Secton 3.

causing endogeneity problem. Equation (2) captures this reverse direction.

Some of the recent research focus on the supply side of the housing market (Glaeser, Gyourko and Saiz (2008), Gyourko (2009)). Suppose there are two cities: city A has higher housing supply elasticity, and city B has a lower one. They have the same housing demand curve. If positive housing demand shocks at the same level comes to the two cities, then the demand curve will shift right for the same level. Holding everything else constant, city A will experience higher quantity increase and lower price increase. Conversely, city B will experience lower quantity increase and higher price increase. Thus housing supply elasticity plays a critical role in the degree and the type of local housing boom.

In the second term of Equation (2), the local housing supply elasticity θ_j, interacted with the national trend of housing boom $\triangle H^{ND}$, is also a determinant of the local housing boom. e_j is a mean zero error term. In this case, housing supply elasticity might be a potential instrument for our purpose.

Many papers argued that the variation of geographical factors and local housing building regulations are two of the sources to explain why housing supply elasticity varied across cities. For example, Saiz (2010), Gyourko, Saiz and Summers (2008). Thanks to the contribution of the authors, such data are available and becoming widely applied in research. In Saiz (2010), the author estimated the local housing supply elasticity as a linear combination of local land unavailability index and local regulation index. The estimated elasticity has very high predictive power on the decadal change of local housing prices. Besides, Saiz (2010) found that the land unavailability index is uncorrelated with many labor supply factors. I employ theses two indexes as instruments to address the endogeneity problem. The identification assumption is that the unobserved local labor supply shock and the unobserved error term are uncorrelated with the two indexes.

Then I try to estimate the equation

$$\triangle L_j = \beta_0 + \beta_1 \triangle H_j + \beta_2 RSH_j + \gamma X_j + u_j \tag{3.3}$$

$$Instrument : Land_j, Reg_j, RSH_j, X_j$$

where X_j are the control variables specified below. The parameters of interest are β_1 and β_2. The instrumental variable strategy provides with identification of β_1. The causal effect of the housing boom demand shock on the local labor market outcome can be estimated.

After I set up the right-hand side, I then put many variables measuring local labor market outcome on the left-hand side. For example, the change in local employment ratio among different populations of interest, and the change in employment share of different occupation groups. By the regressions of the employment share change in all occupations, the parameters β_1 can tell us the housing boom increase the demand for which categories of occupations. And the parameters β_2 can give us a picture of the change of the US labor market structure — how the RBTC shift the labor force from occupations to occupations.

3.2.2 Wage Regression

Besides of the employment share, wage is also an indicator of workers' welfare. If the local housing boom represents a demand shock for the local labor market, we expect positive causal effect of housing boom on workers' wages change. Moreover, we should expect negative causal effect of local routine share on routine workers wages change. This is because higher routine share represents higher potential decline of demand in such routine occupations. On the other hand, the causal effect of local routine share on non-routine workers' wages is a little ambiguous ex ante. If the RBTC shift the labor force from routine occupations to non-routine occupations, then the increase in the supply of the non-routine workers might possibly lower the amount of overall wage raise of the non-routine occupations.

The rich information about individual wage income, occupation, and demographic characteristics in the census data enable us to implement a wage regression. I develop a difference-in-difference type model to estimate the effect of MSA-level housing boom and local routine share on individual wages:

$$w_{ijkt} = \rho_k[\triangle RSH_j \cdot 1(t = 2006)] + \psi X_i + \alpha_t + \delta_j + \phi_k + e_{ijkt} \tag{3.4}$$

where w_{ijkt} is the log weekly labor income of individual i working in occupation k in MSA j in year t. The MSA-level change in routine share between 2000 and 2006, RSH_j, is the variables of interest. Time fixed effect α_t ($t = 2000$ or $t = 2006$), MSA fixed effect δ_j, and occupation fixed effect ϕ_k are included in the regression. X_i are a rich set of individual characteristics which serve as control variables. Our main goal is to estimate ρ_k, the occupation-specific effect.

The empirical results are presented in Section 4.

3.3 Data

3.3.1 Local Labor Market and Local Housing Boom

The major data source for constructing MSA-level labor market variables are 2000 census and 2001-2011 American Community Survey (ACS), which are extracted from the Integrated Public Use Microdata Series (IPUMS) database (Ruggles et.al. (2015)). The census data and ACS data provide with rich information about the individuals taking the survey. Variables such as geographic location, demographic characteristics, education level, employment status, occupation, industry, working hours, and wage income are included in the data set. It's convenient to compute the employment statistics for target populations in target locations. When I calculate the MSA level and national level aggregate employment statistics, each individual is appropriately weighted by his/her census weight. In my specification, a Metropolitan Statistical Area (MSA) is a geographical unit of local labor market. 283 MSAs are identified by the "METAREA" variable in the dataset. METAREA designations are based on 1999 US Office for Management and Budget delineations of MSA. Throughput the paper, I restrict attention to the population aged 18-64, who are the majority of the labor force in the economy. Noncollege workers are defined as the people who never finished at least one year of college study (i.e. EDUC<7).

In the wage regression, weekly wage is used. An individual's weekly wage is calculated as his/her total annual wage income ("INCWAGE") divided by the weeks s/he worked in the whole year. The annual working weeks is the product of his/her usual hours worked per week ("UHRSWORK") and weeks worked in the whole year ("WKSWORK1"). The product of annual working weeks times and individual census weight serves his/her labor supply weight in the wage regression.

I adopt the Housing Price Index (HPI) data from Federal Housing Finance Agency (FHFA), to proxy the degree of the housing boom. Quarterly All-transaction Indexes at the level of Metropolitan Statistical Areas and Divisions are used. Yearly index is obtained by averaging four quarterly indexes in each year. The MSA definition in FHFA is slightly different from that in 2000 census and ACS. I match the HPI to the ACS MSA by hand. As a result, 282 MSAs are matched with HPI data. The housing shock variable $\triangle H_j$, is defined as $log(HPI_{j,2006}) - log(HPI_{j,2000})$.

The land unavailability index and the local regulation index are achieved from Saiz (2010), Gyourko, Saiz and Summers (2008), and Diamond (2016). The land unavailability index was first developed by Saiz (2010). He used geographic information system (GIS) and United States Geographic Service (USGS), to measure the share of the area consisting of steep slopes, oceans, lakes, wetlands, and other water features, in each MSA. The local regulation index was first developed by Gyourko, Saiz and Summers (2008). They sent out a survey to over 6800 municipalities across all major housing markets in the US. Based on the returned respond to the questions on the survey, they integrated a single local land regulatory index. I aggregate the index into the ACS MSA level by simply averaging the indexes of those municipalities which fall into a certain MSA. These two indexes are widely applied in labor economics research, such as Diamond (2016a), Diamond (2016b). The land unavailable index was proved uncorrelated with many local labor supply factor in Saiz (2010), thus it's very suitable to be our instrument. In my paper, the land unavailability index and the local regulation index are matched to 238 MSAs and 251 MSAs, respectively. It reduces the regression sample size when 2SLS estimation is implemented.

3.3.2 Task Measures and Occupation Groups

The data of task contents in each occupation come from the U.S. Department of Labor Dictionary of Occupational Titles (DOT) and O*NET database. Following Autor, Levy and Murnane (2003), Autor and Dorn (2013), I match each occupation with three dimensions of tasks: abstract task, routine task, and manual task. The abstract task measure is the average of two DOT variables: “direction control and planning" and “GED Math". The routine task measure is the average of “set limits, tolerances, and standards" and “finger dexterity". The manual task measure is simply the DOT variable measuring “eye-hand-foot coordination".

To identify a routine occupation, we have to consider how "relatively routine" an occupation is. Suppose there are two jobs. The routine score of the two jobs are identical, but the first job contains more abstract tasks and manual tasks than the second one. Then we should consider the second job is more routine than the first one because workers in the first job have to apply his/her skill to deal with the abstract tasks and manual tasks, hence the full duty of the first job is not all in routine tasks. We call for a measure which values routine tasks and devalues the other two categories of tasks. Following Autor and Dorn (2013), I adopt the summary measure of routine task intensity, RTI, which is computed as:

$$RTI_k = log(R_k) - log(A_k) - log(M_k) \tag{3.5}$$

where R_k, A_k, and M_k are the routine task score, abstract task score, and manual task score, respectively, for occupation k. If an occupation k contains more routine tasks, fewer abstract tasks and fewer manual tasks, then it has a higher RTI index.

Based on the task measures and the nature of the occupations, I classify all 465 3-digit occupations into eight groups. They are high-skill local service, low-skill local service, construction, office administration and support, production, professor, professional, and others. The mean task scores and RTI index are computed for these occupation groups. In Table 3.1, I rank these eight groups by how many shares of these jobs are taken by college-educated workers in 2000.

In Autor and Dorn (2013), their focus is on low-income, low-skill service occupations by the job titles. In my paper, the local service occupations I define here are in a broader sense than they did. I pick the occupations into the local service group by the criterion that people working in these occupations directly offer service to the local consumers, and the service is relatively nontradable to the consumers far away. For example, a waiter working in Lawrence can only serve the people who walk in this Lawrence restaurant, but s/he can not serve a person eating in New York. And a kindergarten teacher in Kansas City cannot take care of a 5-year-old kid in Boston. On the other hand, the items produced by a assembly line worker can be shipped to any corner of the world. And a trader in Wall Street can take transaction orders from Wichita.

What's more, the local service group I define here covers not only low-skill jobs, but it also covers high-skill jobs. For example, social service workers are usually required a degree majored in social work. Before becoming a doctor, a person needs to go to medicine school to receive comprehensive training. I separate these occupation into high-skill service group and low-skill service group based on the college ratio. Surprisingly, the high-skill local service occupations have the highest college ratio among all occupations.

For the rest of the high-skill jobs, some of them contain considerable routine tasks, while others do not. According to this criterion, I divide the rest of the high-skill jobs into two groups: professional and professor. As we see, the professor group consists of architects, engineers, and researchers in life, physical, and social science. Surprisingly, these occupations have an above-average routine task score. The professional group consists of managers, business operators, financial specialists, programmers, legal practitioners, and media practitioners. All of these occupations contain less routine content than an average job.

The most routine intensive occupations are office administration and support, and production. In fact, they are the only two occupation groups whose RTI scores are higher than the average overall RTI score and are positive. All other occupation groups has a below-average RTI score. Assembly line work, text typing, record sorting, and printing machine operation seem to be greatly exposed to the technology shock. It's natural to conjecture that the employment share in these two occupations are facing very large negative shock by the RBTC.

My interest is also on the construction workers, since the demand shock to these workers generated by the housing boom should be quite big— You need to hire people to build. Construction workers take a heavy load of manual tasks. Most of them don't have a college degree. In fact, the manual task score of the construction group is the highest among all bold-face occupation groups.

If we compare the college ratio of each occupation group with the overall college ratio, we can identify high-skill service, professor, and professional as high-skill jobs. The remaining occupation groups are identified as low-skill jobs. Generally speaking, the abstract task scores of high-skill jobs are pretty high. All of them have an above-average abstract task scores. As comparison, all low-skill occupations have a below-average abstract task scores, except for the retail sales occupation. Besides, low-skill jobs contain more manual contents, and the manual task scores of high-skill jobs are usually lower.

Figure 3.4, Figure 3.5, and Figure 3.3 in the appendix section shows the national aggregate employment shares in these occupation groups during 2000-2011. After 2006, the housing bubble burst, and the Great Recession came. So we should expect a downward trend of the employment share after 2006. Figure 3.3 verifies this conjecture. The national employment share in construction occupation increased quite a bit during 2000-2006, from 3.8 percent to 4.4 percent. About 1.9 million people are employed as a construction worker during these period. Of course, the construction bubble burst after the housing bubble burst. The employment share in construction dropped drastically staring from 2006. In 2011, the employment share was even lower than the 2000 level.

Figure 3.4 tells another story. The employment share in office administrative support, production, and professor experienced a decadal decline since the 21st century. Even during 2000-2006, the housing boom period, the employment didn't show a trend of growth. As mentioned above, these occupations contain relatively more routine tasks. When the RBTC theory predicts the declining demand of routine occupations, my empirical analysis will test the RBTC effect on these occupations. The effect of the housing boom and the RBTC will also be untangled: did housing boom contributed anything to boost at least some of the employment opportunities in these occupations?

Oppositely, the employment in local service jobs was strong. As Figure 3.3 shows, the upward trend of the employment share in local service didn't stop until 2008. Even though the employment went down a little bit after 2008, the employment share in local service in 2011 was higher than the 2000 level. During 2000-2008, approximately 3 million people were employed in high-skill service jobs. This number for low-skill service jobs is even higher: 7.5 million people found jobs in low-skill service occupations. The employment gain in service jobs are substantial, not only in low-skill local service, but also in high-skill local service.

3.3.3 Routine Share

We need to construct a variable which measures the local labor market exposure to the Routine Biased Technological Change. Following Autor and Dorn (2013), I adopt the routine share variable. The routine share RSH_j can be constructed with the task measure:

$$RSH_j = \frac{\sum_{k=1}^{K} L_{jk,2000} 1(RTI_k > RTI^{P66})}{\sum_{k=1}^{K} L_{jk,2000}} \tag{3.6}$$

where $L_{jk,2000}$ is the total working weeks supplied by workers in occupation k in MSA j in year 2000, RTI^{P66} is the 66th percentile of the RTI index among all occupations. The routine share variable measures the portion of the labor supply toward the routine tasks in a city.

According to the theoretical model in Autor and Dorn (2013), if the labor force of a local labor market are more initially concentrated in routine occupations, then the RBTC will have larger effect on the employment shifting in this local labor market. More routine workers will be replaced by automation technology, and these workers will shift to other occupations. Therefore, routine share is a suitable variable to measure the degree of local RBTC shock on occupation groups. It's also an empirical measurement of labor demand shock in equation (1).

Autor and Dorn (2013) suggests that the routine share should be instrumented by RSH_j^*, which is computed as:

$$RSH_j^* = \sum_{m=1}^{M} \frac{L_{jm,2000}}{L_{j,2000}} RSH_{-j,m} = \sum_{m=1}^{M} \frac{L_{jm,2000}}{L_{j,2000}} \frac{\sum_{k=1}^{K} L_{-j,mk,2000} 1(RTI_k > RTI^{P66})}{\sum_{k=1}^{K} L_{-j,mk,2000}} \tag{3.7}$$

The idea is similar to the construction of the Bartik measure (Bartik (1991)). RSH_j^* is the interaction between the labor supply ratio in each industry in MSA j, and the leave-one-out national routine share of each industry. If cyclical, short-term expansion is going through in certain industries in 2000 in MSA j, then RSH_j might not reflect the latent real routine intensity in MSA i, especially when these expansive industries are (non)routine intensive industries. To instrument RSH_j by RSH_j^* can address this issue.

Figure 3.2 shows that the routine share and its instrument are highly correlated. Table 3.3 in the appendix section shows that the predictive power of the instrument is strong.

In the difference-in-difference wage regression model, I also adopt the change in routine share as a right-hand side variable. It's calculated as:

$$\triangle RSH_j = -(RSH_{j,2006} - RSH_{j,2000})$$

A larger decrease of the routine share in an MSA implies more routine workers were replaced by technology, which further implies a larger increase of the automation degree. Thus the opposite of the change in local routine share accordingly measure the advancement of “technological realization".

3.4 Results

3.4.1 Employment Regression

This section shows the primary result of my empirical work. First, let's take a look at the employment regression. The final equation in the 2SLS estimation is:

$$\triangle L_j = \beta_0 + \beta_1 \triangle H_j + \beta_2 RSH_j + \gamma X_j + u_j \tag{3.8}$$

$$Instrument: Land_j, Reg_j, RSH_j^*, X_j$$

The parameters of interest are β_1 and β_2, which represent the effect of housing boom demand shock and the effect of RBTC. The performance of the first-stage regression is presented in Table 3.3 in Appendix section.

First I put the change in employment to population ratio from 2000-2006 at the left-hand side. The result of the full model is presented in column (3) of Table 3.5. As we expect, the local housing boom significantly increased the number of local job positions and raised the employment ratio. The OLS estimate and 2SLS estimate of the effect of housing boom demand shock are basically the same. One percentage log increase of the local housing price boost the total employment ratio by 0.0409 percent. In order to give a more intuitive and straightforward illustration of the coefficient estimates, I compute the standardized effect of the housing boom and the RBTC. The standardized effect of housing boom demand shock is defined as $\hat{\beta}_1(\triangle H^{P75} - \triangle H^{P25})/\bar{L}_{2000}$, where $\hat{\beta}_1$ is the 2SLS estimate of the coefficient, $\triangle H^{P75}$ and $\triangle H^{P25}$ are the 75th percentile and 25th percentile of the log change of HPI among all MSAs from 2000 to 2006, and $\bar{L}_{2000}$ is the mean initial base of the labor market outcome in 2000. The standardized effect of the housing boom demand shock measure the percentage respond of the left-hand side labor market outcome variable in an “average" MSA, if we hypothetically change its housing price increase from 25th percentile to 75th percentile. Similarly, the standardized effect of the RBTC is defined as $\hat{\beta}_2(RSH^{P75} - RSH^{P25})/\bar{L}_{2000}$, where RSH^{P75} is the 75th percentile of routine share among all MSAs in 2000.

The standardized effects are presented in brackets in each regression table. They are presented only when the underlying coefficient estimates are significant. As shown in Table 3.5, the standardized effect of housing boom is 0.0192. That is, in an average MSA, if the local housing boom increased from 25th percentile to 75th percentile, then its increase in employment ratio would have risen by 2.2%.

On the other hand, the 2SLS estimate of RBTC effect is insignificant. The technological change didn't harm the total employment opportunity during 2000-2006. This result fits the theory of RBTC and is in accordance with Autor, Dorn and Hanson (2015). RBTC plays a more important role in shaping the occupational composition structure of the labor market. It push the labor force away from the routinized positions, toward the jobs with less routine intensity. The harm is offset by the gain, so the RBTC effect is not reflected in the overall employment statistic. On the contrary, the sectoral demand shock, such as international trade and manufacturing decline, might increase or reduce the overall labor demand through both direct (sector-targeted) effect and indirect (multiplier) effect. The 2000-2006 housing boom I studied in this paper is also such a sectoral shock.

Then I studied the impact of the housing boom and RBTC on the people with college education. As shown in column (3) of panel (b), the housing boom significantly increase the employment ratio among college population by standardized 1 percent in an average MSA. The effect of RBTC is still insignificant.

As for the population without college education, the housing boom increase the employment ratio by standardized 3 percent. The positive impact of housing boom on noncollege people is larger than that on college people. The cyclical housing market prosperity creates more employment opportunities for the low-skill labor than for the high-skill labor.

Although the RBTC reduced the demand for certain routine occupations, it together with the local housing boom might create the emerging demand for other non-routine occupations. People sacked from the routine occupations might find that the employment opportunity in other non-routine job positions was strong. The insignificant coefficient estimates of the routine share provide us with evidence to support this hypothesis. Next we will take a detailed look into the occupational structure of the US labor market from 2000-2006.

The occupation group most directly facing the housing boom demand shock is the construction. From Table 3.1 we can see that, compared with the overall occupations, construction occupations contain far more manual tasks, and are substantially taken by people without college education. The RTI index is much lower than the average level. Obviously, so far construction work is hard to be completely automated, let alone to be outsourced. If a new building project is launched in a local area, then a number of construction workers must be paid to work in that area. Thus we can think of the construction occupation as a local non-routine job.

Table 3.6 presents the 2SLS estimation result for the employment share in construction. Among the total population, the housing boom increased the employment share in construction by 8 percent. Among noncollege people, the magnitude of the estimated effect is 8.2 percent. Slightly larger.

However, we cannot see significant effect of RBTC on the construction jobs. Although we can see a large point estimate of the RBTC effect on noncollege labor force to move to construction, the standard error is also large. Therefore, although the net employment gain in construction due to the housing boom was strong, the occupational structural shift from routine positions to construction positions was weak and neglectable.

Well documented in the existing research, jobs like telephone operators, file clerks, word processors and typists, assembly line workers, are the most exposed to routinization. These jobs fall into the categories of office and administrative support, and production. In column (1) of Table 3.7, the coefficient estimates of housing boom demand shock and routine share are both strongly significant. The local housing boom strongly increase the local employment share in office support occupations by 2.5 percent. However, the RBTC also has strong effect in office jobs. The effect is negative. The RBTC reduced the demand for these intensively routine jobs, hence decreasing the employment share in office occupation by 2.3 percent.

The RBTC also had negative effect on production occupations. The employment share in production jobs declined by 6.9 percent due to the RBTC.

However, the regression result shows no significant effect of housing boom on these jobs. The point estimate is small, come along with a standard error of similar magnitude. The reason might be that the production workers usually produced tangible items, and they are highly tradable over regions. Thus the production activity need not be held in flourishing local economy.

If we exclusively look at the population without college education, the magnitude of effect on office workers is even larger. The housing boom increased the employment share in office occupations by 5.9 percent. The employment gain was greatly reversed by the RBTC, which reduced the employment share by 4.1 percent. As for the noncollege production workers, the RBTC significantly reduced the employment share by 6.7 percent.

Although both office support occupations and production occupations contain considerable routine tasks, the RBTC effect was stronger for production workers than for office workers. What's more, the housing boom basically had no positive impact on the employment of production workers. Meanwhile, thanks to the housing boom, workers were filled into office administrative positions. The noncollege workers especially benefited from the housing boom, if they successfully got employed in such office positions.

Table 3.8 presents the estimates on professors, professionals, and other occupations. Among high-skill occupations, the category of professors contains relatively more routine tasks, while the professional jobs contain relatively fewer routine tasks. The task content of both of them are very abstract and non-manual. It shows no evidence that the RBTC caused any impact on these jobs. In the perspective of employment gain, the RBTC theory predicts the impact of RBTC should be concentrated on the between shift of low-skill labor (Autor and Dorn (2013)).

The housing boom has significant effect on the professionals, but no significant effect on the professors. The housing boom during 2000-2006 boost the employment share in professional occupation by 2.8 percent.

As for the other occupations, neither housing boom nor the RBTC has any effect on its employment share change. By the nature of these jobs, they are less exposed to the shock from housing market and technological change. For example, farming and extraction jobs are concentrated in certain areas rich in natural resources. This is relatively irrelevant to the housing boom.

After I identify office and administrative support and production occupations as the main occupations under routinization, the next question is where these workers were going to. If the housing market was good in a city, then it might be because the people were getting richer, more native people were getting jobs, or more immigrants were flowing in to compete for the job opportunities. All of these would call for an increasing demand for local service. By local service I mean that the people hired in these positions offer some kind of service directly to the people living in the local community. By nature their output should not be tradable to other far-away places. The service occupations I define are in a very broad sense. I divide them into high-skill local service group and low-skill local service group, by the college ratio of these occupations. Among the low-skill service jobs, some of them are low-pay, low-skill jobs. But the high-skill service jobs are intensively taken by people with college education. In fact, the high-skill local service occupations are ranked #1 by the college ratio.

In Table 3.9, column (1), the coefficient estimate of housing shock and routine share on high-skill local service occupations are both insignificant. On the other hand, the housing boom demand shock and the RBTC both have significant effect on the change in employment share in low-skill local service occupations. The local housing boom contributed to increase the employment share in low-skill local service by 2 percent. The magnitude of the effect of the RBTC was even larger. If a city is initially one percentage more intensive in routine tasks than another city, then during 2000-2006 its increase in employment share in low-skill local service would be 0.1947 percent higher than another city. In other words, approximately 19.5 percent of the labor force in routine positions were shifted to the low-skill local service positions during 2000-2006. In sum, this increased the employment share in low-skill service jobs by 3.3 percent. The gain was substantial.

Table 3.1 tells us that office support and production occupations are low-skill. That is, the college ratio of these occupations are lower than the overall level. More accurately, we can consider office and administrative support as middle-skill jobs, since the college ratio is just a little bit lower than the overall level. These two groups are the most exposed to the RBTC. In fact, the national aggregate employment share in these positions declined in a considerable amount. But these people might find job opportunities in local service position. In fact, the employment gain in low-skill service outpaced the employment loss in these two routinization exposed occupation groups. The sum of the coefficient estimates of the routine share on office support occupations and production occupations is -0.1671. The magnitude is smaller than the estimate on low-skill service, which is 0.1947.

If we focus on the people without college education, then the effect is even larger. Housing boom demand shock increased the employment share in low-skill local service by 2.3 percent, and 4.6 percent of the employment share was dragged to these positions from routine intensive jobs, due to the RBTC.

There are some potential explanations for why the effect is insignificant on high-skill service occupations. First, so far we have not seen any negative effect estimates on high-skill labor [4] caused by the RBTC. In the theoretical model in Autor and Dorn (2013), the automation process is complementary to high-skill workers. Most high-skill worker should benefit from the technological change because it enhances their productivity and efficiency. If no college people were fired in other jobs, then no college people would “shift" to high-skill service occupations. This is not the case for low-skill service occupations since many noncollege workers in office and assembly line lost their jobs.

Second, the speed of the increase in skill supply might be slower than the speed of the increase in skill demand. Because the education requirement for working in high-skill local service is high. A lot of education and training investment must be involved if a noncollege worker wants to transit to high-skill service positions. What’s more, the subject specialization in high-skill jobs are highly diversified. So it is also difficult for college workers to freely transit between occupations. This might explain the insignificant effect of housing boom demand shock on high-skill service occupations.

[4]The coefficient estimates of routine share on professor group and professional group are both insignificant. See Table 3.8.

3.4.2 Wage Regression

When we talk about labor market outcome, change in wage is as important as change in employment. The rich individual information in the census data enable us to examine the housing shock effect and RBTC effect on individual wage change in a very detailed manner. In this section I build a difference-in-difference type econometric model in the individual level. I pool the 2000 census data and 2006 ACS data to implement the wage regression.

$$w_{ijkt} = \rho_k[\triangle RSH_j \cdot 1(t = 2006)] + \psi X_i + \alpha_t + \delta_j + \phi_k + e_{ijkt} \tag{3.9}$$

where w_{ijkt} is the log weekly labor income of individual i working in occupation k in MSA j in year t. The change in routine share $\triangle RSH_j$ is the variable of interest. Time fixed effect α_t ($t = 2000$ or $t = 2006$), MSA fixed effect δ_j, and occupation fixed effect ϕ_k are included in the regression. X_i are a rich set of individual characteristics which serve as control variables. This difference-in-difference type model provides us with clear identification of how the variation of the technological change creates variation of change in wages of each occupations. Our main goal is to estimate ρ_k.

The result of the wage regression complements the employment regression and supports the RBTC theory. From the employment regression, there are no significant effect of the RBTC on the employment change of construction and others occupations. The effects of the RBTC on wages are also insignificant for these two occupations.

On the other hand, the RBTC theory predicts that the technological change is complementary to the high-skill labor. In Table 3.10, the coefficients estimates are significant for all three high-skill occupation groups: high-skill local service, professor, and professional. If an MSA had larger decrease in employment share in routine tasks from 2000 to 2006, which implied that the routine workers are more heavily replaced by technology, then the wages of these high-skill workers would experience higher wage increase. Although the RBTC didn't affect the employment of high-skill occupations, it did boost the productivity of the high-skill workers, hence raising their wages.

Every coin has two sides. The RBTC did harm somebody's welfare, especially the low-skill workers. The coefficients estimates are negative for low-skill local service, office administrative support, and production occupations. Due to the declining demand for hiring people to perform routine tasks, the RBTC significantly reduced the routine workers' wages. Specifically, the production workers experienced larger negative shock than the office workers. The coefficient estimate for office occupations is -0.9897, while the coefficient estimate for production occupations is -1.4439.

Not surprisingly, the RBTC also lowered the wage payment to low-skill workers. From the RBTC theory and the employment regression we know that the majority of those who sacked from routine jobs finally flowed to low-skill service jobs. Therefore, if an MSA had larger decrease in employment share in routine positions, then it implied that more workers would transit from these routine occupations to low-skill local service sector. That is, the supply of low-skill local service workers would increase. It would shrink the wages of this occupation group.

3.5 Conclusion

Stepping into the 21st century, the process of Routine Biased Technological Change and job polarization continued. The RBTC had ongoing impact on the employment structure and the occupational composition of the U.S. labor market. The impact was more significant for the the noncollege labor force. The main routine intensive occupation groups, office administrative support, and production, were largely exposed to the shock of RBTC. The national employment share in these low-skill routine jobs consistently dropped. Even the 2000-2006 housing boom did not boost the employment in production. Noncollege workers were shifted from office and production positions, to low-skill local service positions. The employment gain in low-skill local service from the housing boom and the RBTC was tremendous.

On the other hand, the impact of the RBTC on the college-educated labor force was moderate during 2000-2006. The local routine share had no significant effects on the employment shift between any high-skill occupation groups.

However, because the RBTC improved the productivity of high-skill labor, they gained from the technological advancement in terms of paychecks. The RBTC significantly increased the wages of professionals, professors, and high-skill local service workers. Relatively speaking, the low-skill workers might be less lucky. The process of RBTC lowered the wages of the workers in routine occupations, as well as those who worked in low-skill local service jobs. Technology replaced the routine workers hence reducing the demand for routine jobs. The increasing supply inflow of workers to the service sector was to blame for the declining wages in this sector.

The evolution of the U.S. labor employment structure and occupational composition will proceed. There might be some other stories during the Great Recession and in recent years. This will be left to my further research.

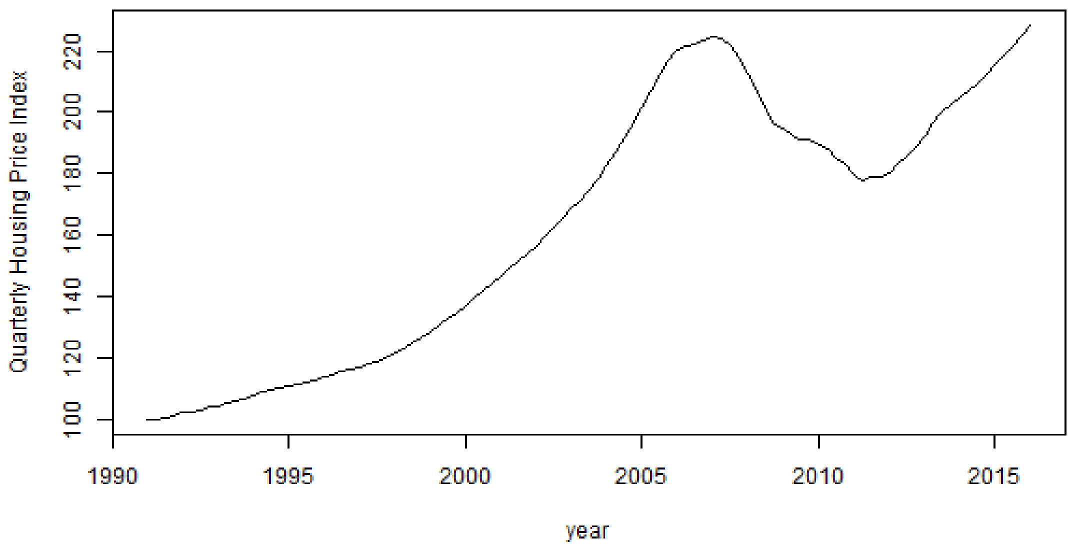


Figure 3.1: Quarterly Housing Price Index 1990-2017

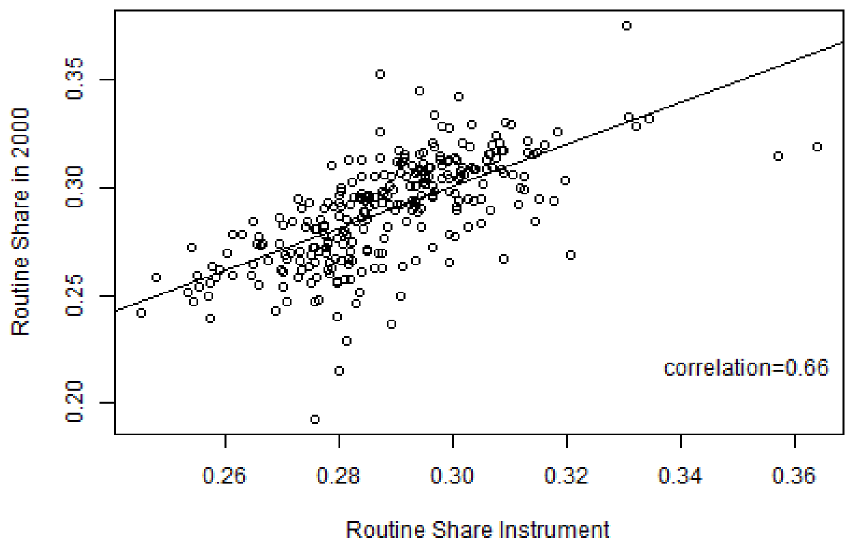


Figure 3.2: Routine Share and Routine Share Instrument

Figure 3.3: Employment Share of Construction Occupation 2000-2011

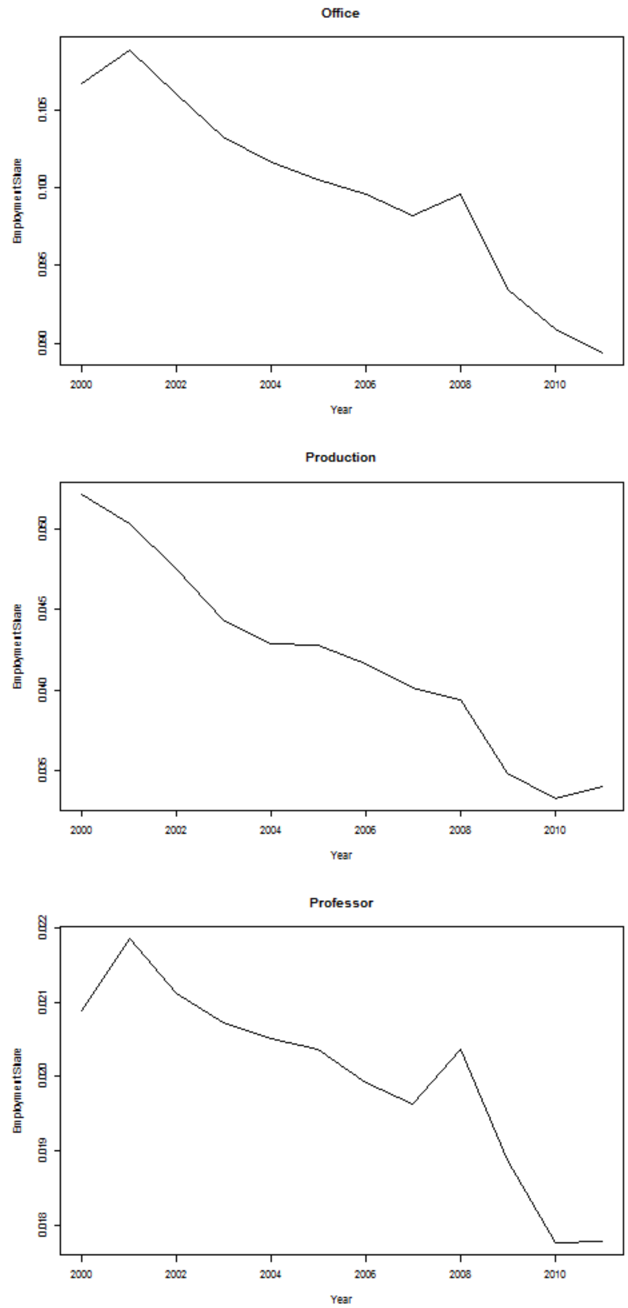


Figure 3.4: Employment Share of Occupations 2000-2011

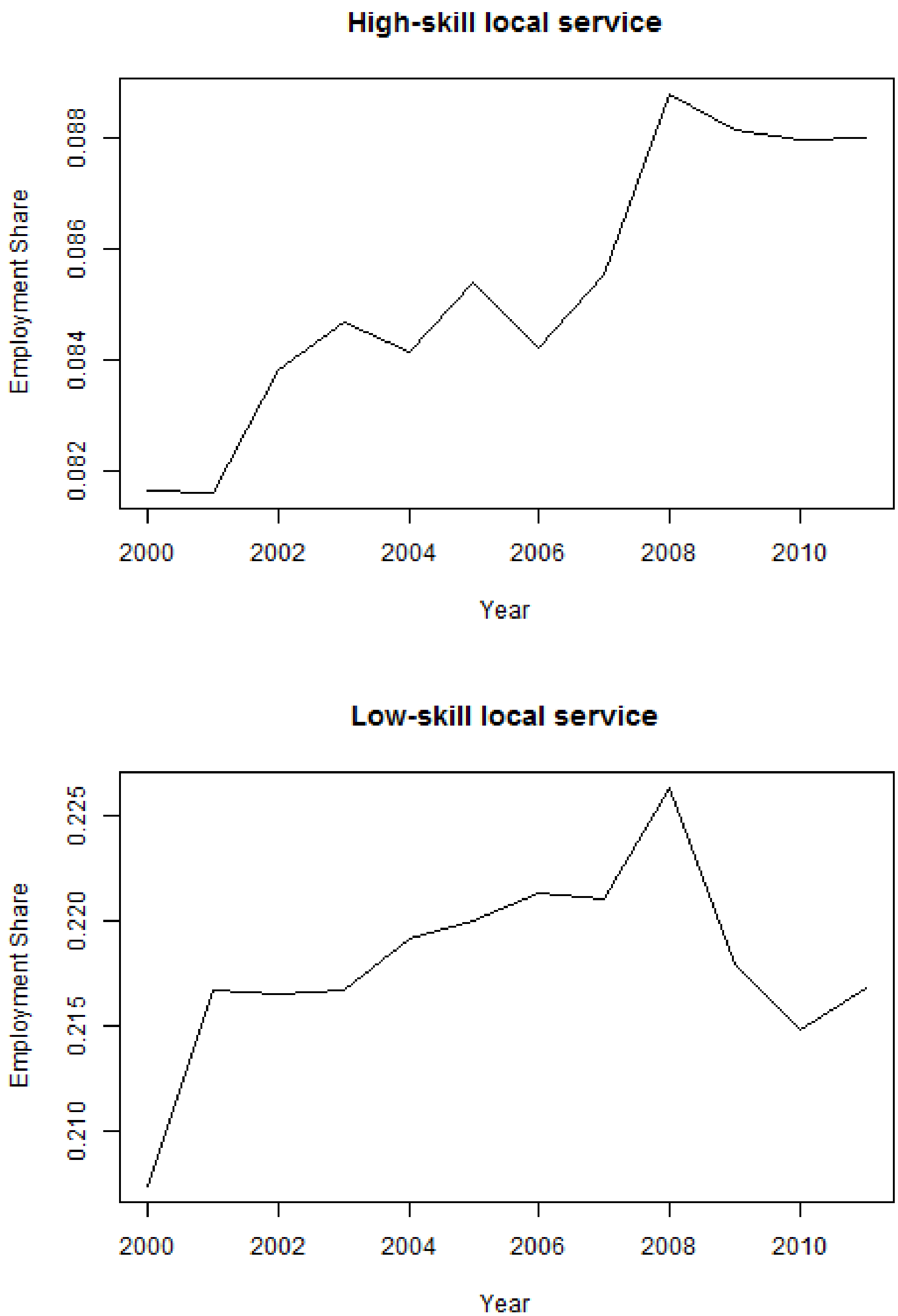


Figure 3.5: Employment Share of Service Occupation 2000-2011

Table 3.1: Task Measures of Occupations

Occupation	Routine	Abstract	Manual	RTI	College ratio	Wage
all	4.37	3.02	1.34	-0.11	0.51	18.99
high-skill local service	3.96	4.36	1.10	-0.38	0.87	21.71
community and social service	1.39	4.42	0.23			
education, training, and library	1.53	7.32	0.26			
healthcare practitioners	5.15	4.33	1.15			
STEM	5.67	6.28	1.09	-0.37	0.86	24.82
architecture and engineering	6.39	7.11	1.44			
life, physical, and social science	4.99	5.49	0.75			
computer and math	3.59	6.00	0.96			
professional	2.75	5.61	0.71	-0.29	0.77	27.04
management	1.89	6.68	0.48			
business operation	2.32	5.68	0.48			
financial specialist	3.56	6.15	0.15			
legal	2.54	3.15	0.08			
art, entertainment, sport, media	3.31	3.69	1.50			
office and administrative support	5.01	1.78	0.19	1.04	0.47	14.00
others	4.86	1.79	2.30	-0.49	0.37	16.71
protective	1.54	1.49	2.97			
farming, fishing, and forestry	2.77	1.17	2.78			
installation, maintenance, and repair	6.87	2.15	1.81			
extraction	4.90	1.19	2.75			
low-skill local service	1.93	2.77	1.79	-0.28	0.35	15.07
healthcare support	3.75	1.59	1.79			
food preparation and serving	2.52	0.97	1.19			
cleaning and maintenance	3.19	1.61	2.25			
personal care and service	2.94	1.99	1.26			
retail sales	2.34	3.14	0.35			
transportation	2.74	1.67	3.21			
production	6.06	1.37	1.07	0.27	0.24	14.86
construction	6.44	1.70	2.94	-0.37	0.23	16.23

Note: The titles of occupation subgroups (not in bold face) are from 1-digit level occupations defined in 2000 census and 2005 ACS. The college ratios and mean wages of workers in each occupations are calculated using 2000 census data. Each individual is weighted by census personal weight and labor supply weight respectively when calculating college ratio and mean wage. The source of occupational task measures are from DOT and O*NET database.

Table 3.2: Summary Statistics of MSA-level Variables

Variable	min	median	max	mean	stand.dev
Change of HPI 2000-2006	0.086	0.339	0.972	0.427	0.227
Routine share in 2000	0.192	0.292	0.375	0.289	0.024
Land unavailability index	-0.024	-0.351	2.824	-1.206	1.012
Local regulation index	-1.677	-0.078	2.179	-0.054	0.772
Routine share instrument	0.245	0.287	0.363	0.288	0.016
Change in employment ratio 2000-2006					
All	-0.094	-0.005	0.090	-0.003	0.027
College	-0.082	-0.014	0.071	-0.013	0.023
Noncollege	-0.111	-0.004	0.109	-0.002	0.036
Change in employment share 2000-2006:					
Construction	-0.016	0.004	0.052	0.004	0.009
Office	-0.041	-0.007	0.022	-0.007	0.010
Production	-0.071	-0.009	0.025	-0.009	0.010
Professor	-0.011	-0.001	0.012	-0.001	0.004
Professional	-0.028	0.000	0.046	0.000	0.010
Others	-0.039	-0.003	0.064	-0.002	0.011
High-skill local service	-0.026	0.001	0.041	0.002	0.009
Low-skill local service	-0.054	0.009	0.062	0.009	0.017

Table 3.3: First-stage Regression

	Housing shock	Routine share
	(1)	(2)
Land unavailability	0.0970****	-0.0011
	(0.0264)	(0.0007)
Local regulation	0.1422****	-0.0007
	(0.0366)	(0.0016)
RSH_i^*	1.1945	1.2593****
	(1.4558)	(0.0865)
F-statistic	46.92	76.7
R^2	0.57	0.69
N	234	234

All regressions include all control variables and are weighted by MSA population in 2000. Standard errors are clustered at state level. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.4: Employment Regression: OLS Estimates

	OLS			
	All			
Dependent variable:	High-skill sevice	Low-skill service	Office support	Production
	(1)	(2)	(3)	(4)
Housing shock	-0.0011	0.0092***	0.0074****	0.0039
	(0.0020)	(0.0037)	(0.0013)	(0.0028)
Routine share	0.0505***	0.1928****	−0.0421**	−0.0770****
	(0.0192)	(0.0411)	(0.0211)	(0.0184)
R^2	0.02	0.38	0.29	0.18
N	282	282	282	282
	OLS			
	All			
Dependent variable:	Construction	Professor	Professional	Others
	(1)	(2)	(3)	(4)
Housing shock	0.0104****	0.0033****	0.0111****	0.0024
	(0.0031)	(0.0009)	(0.0017)	(0.0016)
Routine share	-0.0066	0.0043	-0.0125	-0.0159
	(0.0209)	(0.0084)	(0.0351)	(0.0154)
R^2	0.30	0.07	0.17	0.03
N	282	282	282	282

In all columns, these control variables are included: college share of total population in 2000, female share of employed population in 2000, and the share of white people to total population in 2000. All regressions are weighted by MSA population in 2000. Standard errors clustered at state level are in parentheses. The mean effects are in brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.5: The Effects of Housing Boom and RBTC on Employment to Population Ratio: OLS and 2SLS Estimates

panel (a):	Dependent variable: Employment to population ratio		
	OLS		2SLS
	(1)	(2)	(3)
Housing shock	0.0662****		0.0409****
	(0.0097)		(0.0082)
Routine share		0.1254	-0.0322
		(0.1362)	(0.0846)
R^2	0.43	0.01	0.66
N	282	283	234
panel (b):	**Dependent variable: College employment ratio**		
	OLS		2SLS
	(1)	(2)	(3)
Housing shock	0.0357****		0.0264****
	(0.0047)		(0.0063)
Routine share		0.0771	-0.0063
		(0.0764)	(0.0694)
R^2	0.29	0.005	0.40
N	282	283	234
panel (c):	**Dependent variable: Noncollege employment ratio**		
	OLS		2SLS
	(1)	(2)	(3)
Housing shock	0.0926****		0.0568****
	(0.0168)		(0.0130)
Routine share		0.1702	-0.0222
		(0.1732)	(0.1080)
R^2	0.44	0.006	0.66
N	282	283	234

In column (3), these control variables are included: college share of total population in 2000, female share of employed population in 2000, and the share of white people to total population in 2000. All regressions are weighted by MSA population in 2000. Standard errors clustered at state level are in parentheses. The standardized effects are in brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.6: The Effects of Housing Boom and Routine Share on Employment Share in Construction: 2SLS Estimates

	2SLS	
	All	Noncollege
Dependent variable:	Construction	Construction
	(1)	(2)
Housing shock	0.0093**	0.0133**
	(0.0041)	(0.0063)
	[0.0798]	[0.0823]
Routine share	-0.0337	-0.0245
	(0.0242)	(0.0368)
R^2	0.34	0.33
N	234	234

In all columns, these control variables are included: college share of total population in 2000, female share of employed population in 2000, and the share of white people to total population in 2000. All regressions are weighted by MSA population in 2000. Standard errors clustered at state level are in parentheses. The standardized effects are in brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.7: The Effects of Housing Boom and RBTC on Employment Share in Low-skill Routine Occupations: 2SLS Estimates

	2SLS			
	All		Noncollege	
Dependent variable:	Office support	Production	Office support	Production
	(1)	(2)	(3)	(4)
Housing shock	0.0081****	-0.0001	0.0184****	-0.0007
	(0.0022)	(0.0036)	(0.0036)	(0.0055)
	[0.0248]		[0.0587]	
Routine share	-0.0669^{**}	-0.1002^{****}	-0.1152^{**}	-0.1294^{****}
	(0.0294)	(0.0191)	(0.0584)	(0.0327)
	[-0.0230]	[-0.0686]	[-0.0409]	[-0.0667]
R^2	0.32	0.16	0.28	0.07
N	234	234	234	234

In all columns, these control variables are included: college share of total population in 2000, female share of employed population in 2000, and the share of white people to total population in 2000. All regressions are weighted by MSA population in 2000. Standard errors clustered at state level are in parentheses. The standardized effects are in brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.8: The Effects of Housing Boom and RBTC on Employment Share in STEM, Professional, and Others: 2SLS Estimates

	2SLS		
	All		
Dependent variable:	STEM	Professional	Others
	(1)	(2)	(3)
Housing shock	0.0029*	0.0101****	0.0015
	(0.0016)	(0.0029)	(0.0028)
	[0.0461]	[0.0282]	
Routine share	-0.0042	-0.0075	-0.0261
	(0.0093)	(0.0441)	(0.0246)
R^2	0.08	0.18	0.04
N	234	234	234

In all columns, these control variables are included: college share of total population in 2000, female share of employed population in 2000, and the share of white people to total population in 2000. All regressions are weighted by MSA population in 2000. Standard errors clustered at state level are in parentheses. The standardized effects are in brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.9: The Effects of Housing Boom and RBTC on Employment Share in Local Servce Occupation: 2SLS Estimates

	2SLS		
	All		Noncollege
Dependent variable:	High-skill service	Low-skill service	Low-skill service
	(1)	(2)	(3)
Housing shock	-0.0004	0.0128**	0.0172**
	(0.0028)	(0.0058)	(0.0085)
		[0.0196]	[0.0225]
Routine share	0.0336	0.1947***	0.3128****
	(0.0305)	(0.0619)	(0.0875)
		[0.0334]	[0.0457]
R^2	0.04	0.43	0.49
N	234	234	234

In all columns, these control variables are included: college share of total population in 2000, female share of employed population in 2000, and the share of white people to total population in 2000. All regressions are weighted by MSA population in 2000. Standard errors clustered at state level are in parentheses. The standardized effects are in brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

Table 3.10: Wage Regression: Pooled OLS Estimates

	Wage Regression			
Coefficient ρ_k	High-skill sevice	Low-skill service	Office support	Production
	(1)	(2)	(3)	(4)
Routine share	1.3590^{****}	-1.6900^{****}	-0.9897^{****}	-1.4439^{****}
	(0.2568)	(0.2366)	(0.2297)	(0.2520)
Coefficient ρ_k	Construction	STEM	Professional	Others
	(5)	(6)	(7)	(8)
Routine share	-0.3113	2.4775^{****}	2.1198^{****}	-0.4155
	(0.3431)	(0.4804)	(0.3256)	(0.2642)

The sample include all 2000 census and 2006 ACS individuals who were aged between 16 and 64, lived in metropolitan areas, were not in military, were employed, and gained positive wage income. $N = 4946607$, $R^2 = 0.34$. Housing shock and routine share are instrumented by their respective instruments. Time fixed effect, MSA fixed effect, occupation fixed effect are controlled. Individual level control variables include: race dummy, female dummy, citizen status dummy, education dummy, marital status dummy, English speaking fluency dummy, working disability dummy, foreign born dummy, potential experience, and potential experience squared. The regression is weighted by individual labor supply weight. Standard errors are clustered at MSAs and are presented in parentheses. The standardized effects are in the brackets. (* 0.1, ** 0.05, *** 0.01, **** 0.001)

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