HEALTH REFORM, PHYSICIAN MARKET POWER, AND INCOME DISPARITY

A Dissertation

Presented to the Faculty of the Graduate School

of Cornell University

In Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

by

Sean McNulty Lyons

August 2014

HEALTH REFORM, PHYSICIAN MARKET POWER, AND INCOME DISPARITY

Sean McNulty Lyons, Ph. D.

Cornell University 2014

This dissertation investigates the impact of health reform on both the supply and demand for health services. The first essay analyzes the Massachusetts Health and Insurance Reform of 2006 to determine the impact of employer mandates to offer health insurance to employees. This essay finds that employer mandates are extremely effective in preserving employer sponsored insurance coverage distributions, and that allowing more leniency on smaller firms results in higher take up rates of public insurance for employees in smaller firms. The second essay investigates the extent of market power in specialty physician markets. Whether physicians can exercise market power is becoming ever more salient in the face of health reform. This essay finds evidence that physicians do have market power when bargaining with insurers, and that this market power could lead to higher prices in the private market if physicians are allowed to collaborate on health care provided through the public insurance market. The last essay deviates a bit from health reform and analyzes income differences between persons with and without disabilities. This essay finds that the inclusion of health insurance from both public and private sources as income results in a closing of the income gap between persons with and without disabilities over the last three decades, a reversal of the findings in past literature analyzing these two populations and their economic resources.

BIOGRAPHICAL SKETCH

Sean Lyons received his B.S. from Cornell University in 2007 in Policy Analysis and Management. Following his graduation he worked for the Lewin Group, where he engaged in a variety of health care policy research projects. His time at the Lewin Group incentivized Sean to return to school to study health economics. Sean graduated from Cornell in 2014 with an MA and PhD in economics. While at Cornell Sean studied a variety of topics related to health reform including the Affordable Care Act of 2010 and the Massachusetts Health Reform of 2006. Following graduation Sean accepted a position as a Health Economist with the Congressional Budget Office in Washington, DC.

This dissertation is dedicated to my amazing wife, Kristine, who put up with me throughout my five years in graduate school. God bless her!

ACKNOWLEDGMENTS

This dissertation was partially funded by the U.S. Department of Education, National Institute on Disability and Rehabilitation Research (NIDRR), Employment Policy and Measurement Rehabilitation Research and Training Center, under cooperative agreement H133B100030. I would also like to thank the Lynde and Harry Bradley Foundation for their two year doctoral dissertation fellowship. The findings and conclusions are those of the author and do not represent the policy of the Department of Education or the Lynde and Harry Bradley Foundation. The author retains sole responsibility for any errors or omissions. Lastly, I would like to thank my committee members Rich Burkhauser, Kosali Simon, Will White and Sean Nicholson. I would especially like to thank Rich and Kosali for their tireless efforts in helping me become the economist I am today. It was truly a privilege to work with you both.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1

MANDATED INCENTIVES: THE IMPACT OF FIRM SIZE THRESHOLDS FOR EMPLOYER MANDATES IN MASSACHESETTS

1.1 Introduction

The state of Massachusetts passed sweeping health care reform legislation in 2006 with the Massachusetts Health Care and Insurance Reform Law (MHCI). The reform aimed to expand access to health insurance coverage through a combination of insurance market reforms, individual and employer mandates, and access to health insurance subsidies through the state's Commonwealth Health Insurance Connector Authority (the Connector). A major policy dilemma faced by the federal government and states when attempting to ensure affordable access to health insurance is balancing increased access to public health coverage with public insurance crowd-out of the private market. To preserve the traditional provision of health insurance by employers, the Massachusetts reform implemented firewalls to limit access to subsidies based on family income and availability of employer sponsored health insurance (ESI). In addition to the subsidy access firewalls applied to individuals, the reform mandated that all employers over 11 full time equivalent employees (FTEs) offer and make a "fair and reasonable" contribution to health insurance coverage. The definition of a "fair and reasonable" contribution differed by firm size, allowing more lenient requirements on smaller firms (11 to 50 FTEs). The "fair and reasonable" contribution requirement for small firms allowed them to be in compliance with the employer mandate while simultaneously allowing their employees that were income-eligible for subsidies to choose between subsidized coverage and their employers offered plan. While large-firms that complied with the "fair and reasonable" contribution requirement automatically barred all of their employees from accessing subsidized insurance, even if they were income-eligible. This paper assesses the difference in coverage distributions between lower-income small and large firm employees due the more lenient small firm employer mandate.

This paper shows that the more lenient treatment of small firms provides a clear financial incentive – one not open to larger firms – for small-firm employers and their employees to work together to allow income-eligible employees to access subsidized coverage without affecting the actual cost or access to ESI they provide to employees who are not income eligible. For this reason, the different treatment of small firms is more likely to encourage small-firm employers and their employees to alter their existing health insurance contracts, resulting in a relatively higher share of their income-eligible employees enrolling in subsidized coverage and a relatively lower share being enrolled in ESI coverage than would have been the case had the MHCI treated small and large firms equally under the mandate. That is, there is a trade-off between allowing more leniency for small firms to comply with the employer mandate under the MHCI, and the goal of minimizing coverage shifts from ESI to subsidized health insurance.

Using data from the Current Population Survey (CPS) and a triple-difference analysis, this paper shows the extent to which the MHCI generated differences in the take-up of subsidized coverage and ESI between small- and large-firm employees in Massachusetts. In doing so it assesses the degree to which the more lenient treatment of small firms under the MHCI increased the shift from ESI to subsidized coverage above what it would have been absent this different treatment. Previous analyses of the MHCI have primarily focused on health service utilization, health outcomes, cost, and source of coverage. This paper extends this literature by analyzing the difference in coverage distributions due to the interaction of the employer mandate requirements and access to subsidies criteria by firm size. Thus, this paper provides a richer perspective on the incentives embedded in the reform legislation that potentially alter lower-income employees' pathways to health insurance coverage.

The differences in health insurance coverage distributions between small and large firms are not trivial. Since the enactment of the MHCI in 2006, employees of small firms have generated most of the new subsidized coverage take-up. Of every two newly covered small-firm workers receiving a MHCI subsidy, one would have chosen ESI had he or she been subject to the more stringent large-firm employer mandate. Additionally, there are noticeable differences in the coverage distributions across exempt small firms, small firms subject to the more lenient mandate, and large firms subject to the more stringent mandate. Exempt firms have lower increases in the take up of ESI and higher increases in the take up of subsidized coverage compared to non-exempt firms while non-exempt display the same pattern compared to large firms. Not only do these results highlight the overall effectiveness of an employer mandate, but they also provide evidence that the stringency of the employer mandate has a significant impact ESI and subsidized coverage take up rates.

These findings are the first to empirically show that treating income-eligible small-firm employees differently than similar employees in large firms will have a different effect on employees' movement onto subsidized coverage instead of ESI. This has important implications for the ACA, which includes very similar reform elements with respect to subsidy access for workers and more lenient mandates on smaller firms. The similar employer mandate structure and access to subsidy criteria in both the MHCI and the ACA underscores the policy relevance of studying the extent to which the MHCI altered the previously existing pathways to health insurance coverage for lower-income workers. Additionally, the ACA's employer mandate has been postponed until 2015 to allow firms more time to adjust their health insurance benefit packages. The removal of such a mandate serves to exacerbate the coverage shifts that would have occurred under the original ACA employer mandate.

This chapter proceeds as follows: Section 1.2 provides an in-depth review of the relevant features of the MHCI; Section 1.3 provides an outline of my hypotheses; Section 1.4 discusses the data used to empirically estimate the different treatment effects; Section 1.5 is a discussion of my identification strategy; Section 1.6 previews the robustness checks I perform on my baseline estimates; Section 1.7 displays the results of my estimation; and Section 1.8 concludes with a summary of my results and a discussion of my findings.

1.2 Massachusetts Health Reform

Massachusetts was the first state to pass legislation to achieve near-universal coverage through "incremental universalism" in April 2006 (Gruber, 2008). Gruber (2010) described the Massachusetts Health Care and Insurance Reform Law of 2006 as a "Three-Legged Stool." The first leg of the stool is comprised of insurance market reforms, which includes guaranteed issue, community rating, and a merge of the non-group and small-group markets. The second leg mandates that individuals obtain and maintain health insurance coverage and that employers offer health insurance to all full-time employees and make a "fair and reasonable" contribution to such coverage. The third leg of the stool provides subsidized and unsubsidized coverage through the state's Commonwealth Health Insurance Connector Authority (the Connector) to Massachusetts residents, with subsidies available to individuals below 300 percent of the FPL. The first leg aimed to reduce premiums in the small and non-group markets by merging the two and allowing for a larger risk base; it also sought to guarantee that individuals could obtain health insurance coverage despite pre-existing conditions. The individual mandate of the second leg serves to safeguard against adverse selection by not allowing healthy individuals to forgo coverage without a financial penalty, while the employer mandate of the second leg aimed to ensure that the traditional provision of ESI remained the primary source of health insurance coverage for the working population in Massachusetts. Lastly, the third leg of the stool offers publicly subsidized private health insurance plans in order to provide individuals below 300 percent of the FPL who otherwise cannot obtain Medicaid or ESI an opportunity to purchase affordable health insurance coverage.

The Connector began offering subsidized coverage to residents in the 100-to-300-percent FPL range beginning in February 2007. The requirement that individuals maintain health insurance coverage took effect on July 1, 2007 and imposed a penalty of $219 for non-compliance. This penalty was subsequently increased in 2008 to 50 percent of the lowest cost health insurance premium available each month through the Connector. The requirement that firms of 11 or more full-time-equivalent (FTE) employees offer health insurance to all full-time employees and make a "fair and reasonable" contribution to such coverage was finalized on June 29, 2007. Thus, the main elements of the health reform law were in place at the start of the 2008 calendar year. Massachusetts also expanded Medicaid coverage for children in families up to 300 percent of the FPL as part of the 2006 reform, but chose not expand adult Medicaid (MassHealth) and kept eligibility for adults at 133 percent of the FPL throughout the health reform implementation. However, Massachusetts did increase enrollment caps for previously eligible adults on the MassHealth waiting list, which increased adult Medicaid enrollment from 1.3 million in 2006 to 1.6 million in 2008.[1] I compared the average number of Massachusetts workers below 133 percent of the FPL enrolled in Medicaid for years 2000-to-2005 to years 2006-to-2011 using CPS data and found that average adult Medicaid enrollment increased by roughly 22,500 from the period covering 2000-to-2005 to the period covering 2006-to-2011, which indicates that the bulk of the increase in Massachusetts Medicaid roles came from the non-working poor.

The individual mandate to obtain and maintain health insurance coverage can be met by either enrolling in Medicaid, enrolling in ESI, or obtaining coverage through the Connector. Workers

[1] http://www.medicaid.gov/Medicaid-CHIP-Program-Information/By-State/massachusetts.html

above 133 percent of the FPL cannot enroll in Medicaid and must seek coverage through either their employer or the Connector. The Connector offers subsidized insurance coverage through Commonwealth Care to individuals below 300 percent of the FPL who are not eligible for MassHealth (Medicaid). Additionally, through Commonwealth Choice, the Connector offers unsubsidized coverage to any resident not qualified for MassHealth or Commonwealth Care. An income-eligible worker (between 133 and 300 percent of the FPL) and his or her dependents are allowed to access subsidies on the exchange if the worker's employer either does not offer health insurance or offers coverage but contributes less than 33 percent of the annual premium cost of an individual health insurance plan or less than 20 percent of a family health insurance plan. Individuals eligible for subsidized coverage through the Connector receive subsidies on a sliding scale based on their FPL. In 2013 individuals below 150 percent of the FPL received fully subsidized health insurance; individuals between 150 and 200 percent of the FPL could choose from a list of plans with monthly premiums between $40 and $81; individuals between 200 and 250 percent of the FPL faced monthly premiums between $78 and $138; and individuals between 250 and 300 percent of the FPL faced monthly premiums between $118 and $182.[2]

The employer mandate can be separated into two distinct requirements, the first of which is the requirement to offer an ESI plan in which employer and employee contributions are tax exempt (section 125 plan). The second requirement is that employers make a "fair and reasonable" contribution to their employees' health plans. Employers with 11 or more FTE employees who fail to offer a section 125 plan are subject to the "free-rider surcharge." This penalty is assessed as a percentage of the dollars spent by the health safety net fund that can be attributed to a specific employer's employees and dependents. The percentage is higher for

[2] 2013 premiums available through https://www.mahealthconnector.org.

firms of more than 50 FTE employees compared to firms of 11 to 50 FTE employees.[3] Employers can avoid the “free-rider surcharge” as long as they offer a section 125 plan, independent of whether or not they subsidize coverage. The Massachusetts Division of Health Care, Finance, and Policy (2013) notes that 93.9 percent of firms with 11 or more FTEs offered section 125 plans in 2011, but no firm has had to pay the “free-rider surcharge” since MHCI implementation because the employees in non-compliant firms have never breached the health care cost thresholds at which the fine is assessed. Thus, for the purposes of this paper I will assume that all firms are in compliance with the section 125 plan requirement.

The second part of the employer mandate requires employers with 11 or more FTE employees to make a “fair and reasonable” contribution to their full-time employees’ health insurance premiums. The “fair and reasonable” contribution requirement does not apply to firms with fewer than 11 FTE employees, and its requirements differ for firms with 11 to 50 FTE employees as compared to firms with more than 50 FTE employees. There exist two basic criteria that comprise the “fair and reasonable” contribution requirement:

1. The employer offers health insurance coverage and contributes at least 33 percent of the total annual single coverage premium cost.

2. The employer offers health insurance coverage, and at least 25 percent of the employer’s full-time employees are enrolled in the offered plan.

Firms with 11 to 50 FTE employees can meet the “fair and reasonable” contribution requirement by satisfying one of two criteria listed above. Firms with more than 50 FTE

[3] For costs incurred in the range of $50,000-$75,000, firms sized 11-25 are fined 20%, firms sized 26-50 are fined 50%, and firms with more than 50 FTE employees are fined 80%. For costs incurred in the range of $75,001-$150,000, firms sized 11-25 are fined 30%, firms sized 26-50 are fined 60%, and firms with more than 50 FTE employees are fined 90%. For costs incurred in excess of $150,000, firms sized 11-25 are fined 40%, firms sized 26-50 are fined 70%, and firms with more than 50 FTE employees are fined 100%.

employees can satisfy the “fair and reasonable” contribution requirement by either complying with both criteria listed above or demonstrating that at least 75 percent of their full-time employees are enrolled in the offered health insurance plan. Independent of firm size, any employers who fail to meet the “fair and reasonable” contribution requirement are fined $295 annually per FTE employee. The Massachusetts Division of Health Care, Finance, and Policy (2013) notes that roughly 93 percent of firms sized 11-to-25 and 96 percent of firms sized 26 and over were in compliance with the “fair and reasonable” contribution requirement in 2011. Additionally, Massachusetts collected $18.4 million from non-compliant firms in 2011, with 22 percent of the contributions coming from small firms (11-50 FTEs) and 78 percent coming from large firms (51+ FTEs) (Massachusetts Division of Health Care, Finance, and Policy, 2013).

Combining the subsidy eligibility and employer mandate criterion results in the ability of small firms (11-50 FTEs) to satisfy the “fair and reasonable” contribution, while still allowing their income-eligible employees access to subsidies through the Connector. Small firms achieve this by demonstrating that at least 25 percent of the firm’s full-time employees are enrolled in the firm’s offered plan to which the firm contributes less than 33 percent of the total annual single-coverage premium cost. Large firms in compliance with the “fair and reasonable” contribution requirement categorically disqualify their income-eligible employees from accessing subsidies through the connector because they must meet the first requirement of contributing at least 33 percent of the total annual single coverage premium cost. This feature of the MHCI is made clear though Figures 1.1, 1.2, and 1.3 which display the decision trees under the MHCI for exempt firms, small-firms, and large-firms, respectively. Figure 1.1 displays the choices available to exempt small-firms. Due to their exemption there is no incentive to change their existing contracts with employees to allow their income eligible workers to access subsidies through the Connector. Figure 1.2 displays the choices available to non-exempt small-firms. If these firms choose to alter their existing employment contracts, it is clear that allowing their income eligible employees to access subsidies is the dominant choice. Lastly, Figure 1.3 displays the choices available to non-exempt large-firms. The only way large firms can allow their income eligible employees to access subsidies to be not be in compliance with the “fair and reasonable” contribution requirement, thus the incentive to engage in such behavior is dependent upon the distribution of full time workers income within the firm. Therefore, under the MHCI employer mandate it is always a dominant decision for non-exempt small-firms to allow their employees the option to choose between ESI or subsidized Connector coverage, while large firms must weigh the cost incurred from fines of allowing their income eligible employees to access subsidies.

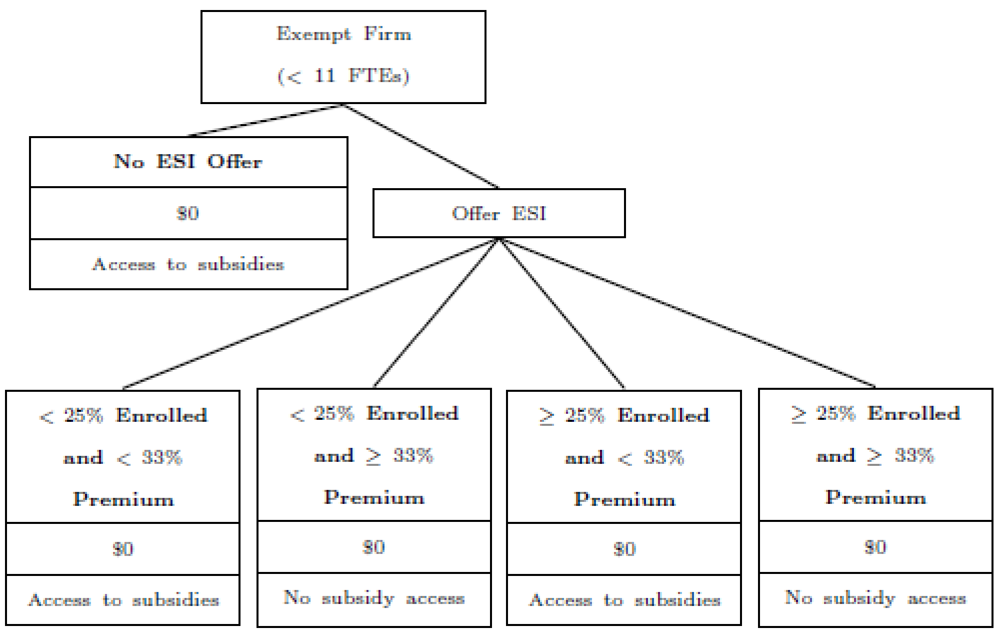


Figure 1.1: Decision Tree for Exempt Firms

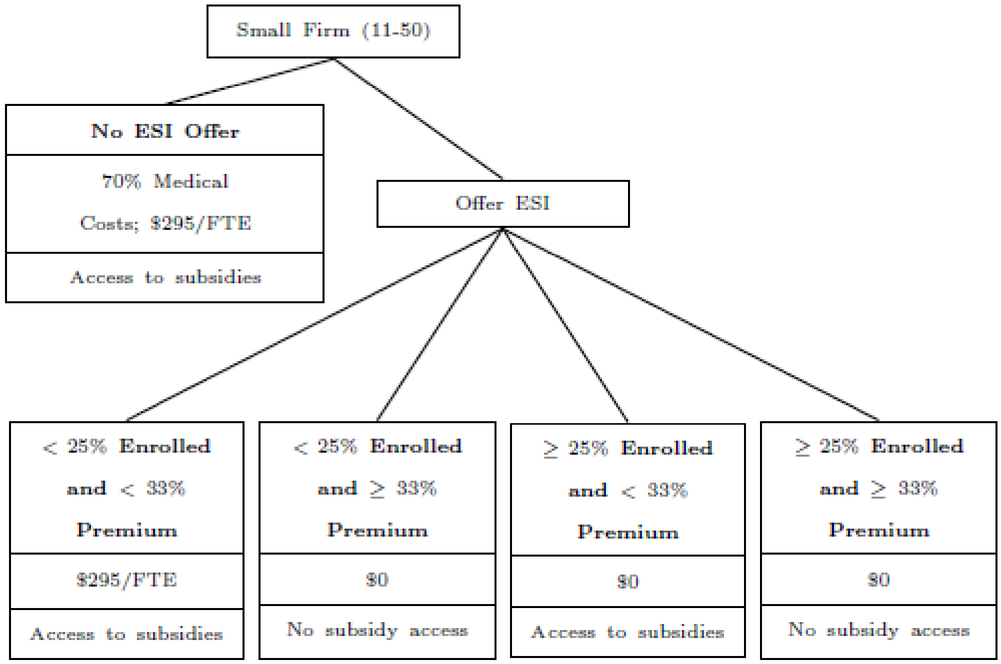


Figure 1.2: Decision Tree for Small Firms

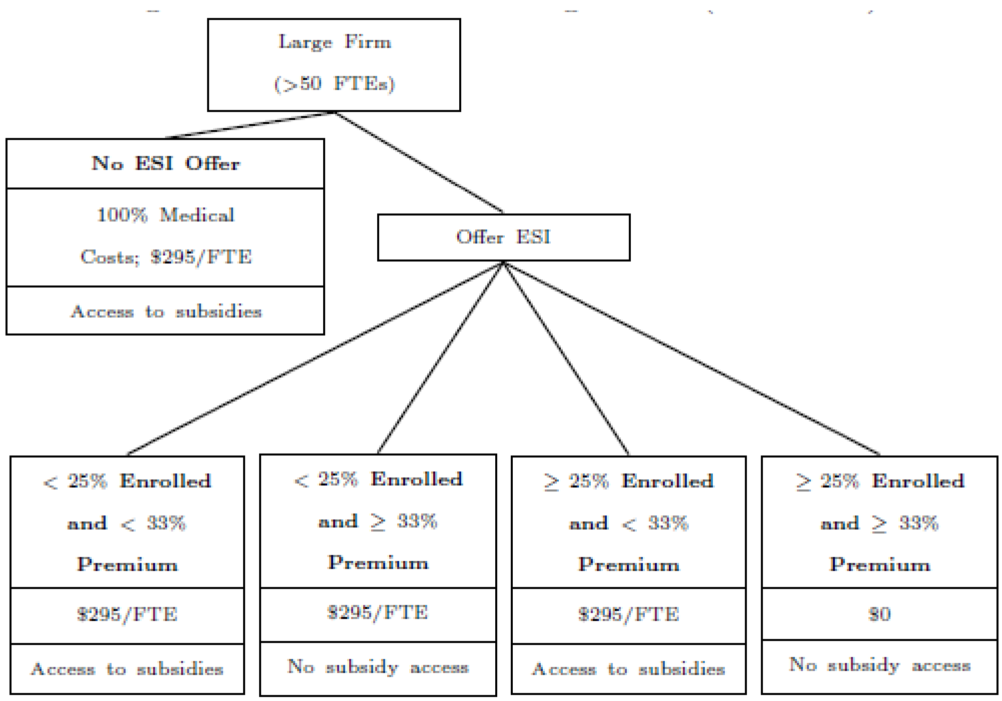


Figure 1.3: Decision Tree for Large Firms

The mechanism through which small firms can allow their income eligible employees the choice between ESI and subsidized Connector coverage without affecting their economic welfare is that small-firms can require that their employees contribute a greater share of the premium contribution without any economic harm to the employee. The split between employer and employee contributions under the MHCI is completely artificial when the provision of health insurance is considered to be a part of the overall employees' compensation package (Brown, 1980; Summers, 1989). Employers can require employees to contribute a higher share of the premium while passing back the increased contribution requirement in wages. The transfer of the premium contribution share from the employer to the employee maintains the plan's tax-exempt contribution status due to the mandate on firms to offer section 125 plans or be subject to the "free-rider surcharge." Therefore, small firms can be in compliance with the employer mandate to offer and contribute to their employees' health plans while allowing their income-eligible employees to decide between their employer-sponsored tax-exempt contribution plan or increased wages (taxed) and a subsidized plan. Under this scenario, the employee is no worse off economically than when his or her employer contributed a higher share of the premium, and the employee is free to choose either ESI or subsidized coverage along with increased wages that are taxed at the employee's marginal tax rate.

The existing literature covering the MHCI has not explicitly addressed the coverage impacts due to the different application of the employer mandate by firm size. The effect of the Massachusetts health reform with respect to health care service utilization, health outcomes, cost, and source of coverage have been investigated. The Massachusetts Division of Health Care, Finance, and Policy (2011) estimates that the percent of uninsured Massachusetts residents had fallen to 1.9 percent by September 2010, which is congruent with the finding of Long et al. (2009) of a significant decrease in uninsurance rates in Massachusetts. With respect to health services utilization, Long et al. (2012) find a significant increase in individuals reporting a usual source of care; Long and Stockley (2011) note a significant decrease in unmet medical needs; and Kolstad and Kowalski (2012a) find a significant increase in the use of primary and preventive health care services in conjunction with a small decrease in hospital admissions deemed preventable with quality outpatient care. Courtemanche and Zapata (2012) addressed the impact of the Massachusetts reform on self-reported health status and find that Massachusetts residents are more likely to report their health as "very good" or "excellent." Raymond (2009) cites that the federal government funds half of the $707 million annual cost of the MHCI. Kolstad and Kowalski (2012b) find that employers have almost fully adjusted real wages to offset the increased cost of health insurance post-MHCI implementation.

The MHCI drew a significant amount of attention in both media and academic circles and eventually became the inspiration and foundation for national health reform embodied in the ACA. Early research finds that the MHCI succeeded in substantially increasing health insurance coverage with little-to-no subsidized insurance crowd out of ESI (Long, 2010; Kolstad and Kowalski, 2012a; Blue Cross Blue Shield of Massachusetts, 2012). These studies find that in Massachusetts, both ESI and publicly subsidized insurance coverage increased subsequent to the implementation of the MHCI. The increases in both public and private coverage are congruent with the structure of the MHCI, which expands access to health insurance through employer mandates, individual mandates, and the creation of a subsidized health insurance option through the state-run Connector. The coverage shifts discussed in this paper differ from the concept of crowd out. In fact, the results presented in this paper support the previous findings of no crowd out, even among the income-eligible working population. Coverage shifts occur under the MHCI when a small-firm employee obtains a subsidy for health insurance when he or she otherwise would have obtained or maintained ESI under the counterfactual scenario in which small firms are subject to the more stringent large-firm employer mandate. Thus, the concept of coverage shifts embodies how pathways to coverage for lower-income workers have changed due to the implementation of an employer mandate that differs by firm size.

A major achievement of the MHCI was to increase state-wide health insurance coverage rates by providing incentives for employers to offer coverage, employees to purchase coverage from their employer, and those without access to ESI to take-up either Medicaid or subsidized insurance. In light of these achievements and the planned implementation of "Massachusetts-like" national health reform in 2014, it is important to further the health reform literature by investigating the extent to which pathways to health insurance coverage have changed due to specific MHCI policy parameters that have been built into the ACA. This paper achieves this goal by using the interaction of the MHCI's firm-size-dependent employer mandate and access to subsidies criteria to identify coverage shifts from ESI to subsidized insurance for small-firm employees.

1.3 Hypotheses

Traditionally, federal and state labor-market regulations have built in a firm-size-dependent component that imposes more lenient restrictions on smaller firms, and Massachusetts was not an exception when policy makers crafted the MHCI for implementation in 2006.[4] This seemingly benign feature of the MHCI potentially affects a non-trivial fraction of Massachusetts workers in that the small-firm market sector accounted for 25 percent of private-sector-employed individuals and 74 percent of all firms in Massachusetts in 2012.[5] More lenient mandates on small firms can lead to asymmetric behavioral responses across small and large firms by allowing small firms to take advantage of exemptions. For the MHCI, this would manifest in noticeably greater numbers of small-firm employees joining the subsidized coverage rolls and significantly fewer small-firm employees taking up ESI relative to large-firm employees.

The MHCI allows small firms to be in compliance with the employer mandate and still provide their income-eligible employees the option of either accessing subsidized coverage or choosing the firm's ESI plan, without decreasing their employees' economic welfare. This is not the case for large-firm employers. This structure provides an incentive for small firms to

[4] For example, The Family and Medical Leave Plan exempts firms with fewer than 50 workers; the Americans with Disabilities Act exempts firms with fewer than 15 workers; the Worker Adjustment and Retraining Notification Act exempts firms with fewer than 100 workers; the Occupational Safety and Health Act exempts firms with fewer than 11 workers; the Age Discrimination in Employment Act exempts firms with fewer than 20 workers; the Civil Rights Act of 1964 exempts firms with fewer than 15 workers; the Fair Labor Standards Act exempts firms with fewer than 3 workers; and the Occupational Safety and Health Administration (OSHA) exempts firms with fewer than 11 workers from regular programmed inspections.

[5] 2012 Medical Expenditure Panel Survey-Insurance Component Summary Tables.

allow their income-eligible employees access to subsidized coverage through the Connector, which reduces the marginal costs of employing lower-income workers, thus placing the burden of health insurance coverage onto taxpayers. Furthermore, there were roughly 130,000 income-eligible small-firm employees in Massachusetts in 2011 who could potentially access subsidies of up to $5,000 annually for a single-coverage health plan.[6] Thus, allowing small firms to send their income-eligible employees to the Connector for subsidized coverage when they otherwise would have taken up ESI under a more stringent employer mandate may result in significantly higher costs to the state and federal government.

The MHCI provides incentives for employers to offer insurance coverage and employees to take-up insurance coverage. Additionally, Massachusetts created a new state-run entity (the Connector), which offers subsidized coverage to income- and categorically-eligible individuals. These policy parameters should result in increases in ESI, subsidized coverage, and overall insurance rates. This result has been documented by several studies (Long, 2010; Kolstad and Kowalski, 2012a; Blue Cross Blue Shield of Massachusetts, 2012). Despite the overall increases in ESI, subsidized coverage and overall insurance rates, there exists an incentive for employers to get their income-eligible employees onto the subsidized coverage rolls in order to transfer the cost of health insurance from the employer and the employee to taxpayers. Massachusetts mitigated the extent to which workers could access subsidized coverage plans through the Connector by imposing several firewalls to accessing subsidies. First, the MHCI imposes income-eligibility criteria limiting subsidies to those with family incomes in the 133-to-300 percent of the FPL range. Additionally, the MHCI imposes a categorical requirement that individuals seeking subsidies either must not have access to ESI or have access, but the employer contributes less than 33 percent of the annual premium cost

[6] Subsidies depend upon age, locality, and FPL. Subsidy estimate based on the annual unsubsidized premium cost for an individual health plan through the Commonwealth Choice program in 2013.

of an individual health insurance plan or less than 20 percent of a family health insurance plan. This categorical firewall prevents workers from taking up subsidized coverage when they have access to insurance through their employer. A small-firm worker can overcome this firewall much easier than a worker in a large firm can, due to the different application of the "fair and reasonable" contribution requirement for small firms compared to large firms.

The difference in the application of the "fair and reasonable" contribution requirement for small firms compared to large firms creates an environment in which it is easier for small firms to be in compliance with the requirement, while the fine for non-compliance is the same for all firms larger than 11 FTEs.[7] Firms with fewer than 11 FTE employees can choose to simply drop coverage altogether and allow all of their income-eligible employees access to subsidies, facing no penalty for doing so. As discussed above, firms with 11 to 50 FTE employees can be in compliance with the "fair and reasonable" contribution requirement and allow their income-eligible employees access to subsidies, while firms with more than 50 FTEs cannot engage in such behavior and still satisfy the "fair and reasonable" contribution requirement.

The different application of the "fair and reasonable" contribution requirement can be likened to a world in which different speed limits exist for trucks and cars, while the fine for speeding is identical for both vehicle types. In such a world a policy maker might change a universal speed limit of 30 miles per hour to one in which trucks are considered to be speeding if they travel above 30 miles per hour and cars are considered to be speeding if they travel above 50 miles per hour, while leaving the penalty for speeding at $100 for both trucks and cars. In this world one would expect to observe an increase in the fraction of cars traveling between 30 and

[7] The "free-rider surcharge" does vary by firm size, but no firm has been subject to the fine since the implementation of the MHCI, thus I will ignore this aspect of the law.

50 miles per hour relative to trucks because there is no financial penalty for car drivers who drive under the 50-miles-per-hour speed limit. Although the MHCI is more complex than this stylized example, the basic intuition is still relevant. Under the MHCI it is easier for small firms to take advantage of the incentive to send their income-eligible employees to the Connector for subsidized coverage than it is for large firms. Therefore, I would expect small-firm employees to be more likely than large-firm employees to join the subsidized coverage rolls. Following the same logic, I would expect relatively fewer small-firm employees to take-up ESI compared to large-firm employees. The hypothesis that small-firm employees will increase their take-up of subsidized coverage and decrease their take-up of ESI relative to large-firm workers leaves a theoretically ambiguous outcome for the impact on overall insurance rates between small and large firms. Empirical evidence is needed to determine which effect is larger in absolute value.

1.4 Data

I use Current Population Survey (CPS) data corresponding to years 2000-to-2011 to analyze the extent to which the different application of the MHCI employer mandate by firm size differently affected health insurance coverage distributions between small- and large firm-employees. I compare Massachusetts insurance outcomes to insurance outcomes in a set of control states by firm size. The main control group consists of the Northeastern states: Connecticut; Washington, DC; Delaware; Maryland; Maine; New Hampshire; New Jersey; New York; Pennsylvania; Rhode Island; and Vermont.

I limit the CPS data to private-sector workers of ages 18 to 64 who are between 133 and 300 percent of the FPL, employed at work, and not receiving any SSI or SSDI benefits.[8] This

[8] FPL calculated by the author using family income, family size, and the U.S. Department of Health and Human Services poverty guidelines for each year.

limitation allows me to focus on the population that is income-eligible for subsidized coverage, thus isolating the relevant group of workers whose health insurance coverage choice would be affected by the firm-size-dependent employer mandate. I also look into the treatment effect in Massachusetts for workers above 300 percent of the FPL as a falsification test.

The CPS does not assign firm sizes by FTE employee, but by the number of employees in a firm. In addition, its firm size gradations do not line up perfectly with the regulations in the MHCI. Ideally, firm size would be reported so that I could identify workers in firms sized 1 to 10, 11 to 50, and more than 50. However, I can identify firms sized 1 to 10, 11 to 24, 25 to 99, and 100 or more. My main analysis defines small firms as firms sized 1 to 24 and large firms as firms sized 25 and over. This is an unavoidable data limitation, which poses a threat to my identification strategy. To partially address this issue, I investigated firm-size distributions in Massachusetts using the MEPS-IC. My baseline analysis of firms sized 1 to 24 compared to firms 25 and over assigns firms with 25 to 50 employees to the large-firm group, which is not congruent with MHCI regulations. According to the MEPS-IC, firms sized 1 to 50 in Massachusetts represent about 26 percent of all employees, of which 6 percent fall into the 25 to 50 size group.[9] Thus, most small-firm employees (80 percent) are represented by the 1 to 24 size group. Also, the number of small firms sized 1 to 50 in Massachusetts represents roughly 75 percent of all firms, of which 5 percent fall into the 25 to 50 category. Thus, most small firms (93 percent) are represented by the 1 to 24 size group. Despite the issues posed by the firm-size categories represented in the CPS, the relatively small percent of firms sized 25 to 50 and the small percent of employees working in firms sized 25 to 50 serves to mitigate this

[9] Using the CPS subsample of workers in Massachusetts between 133 and 300 percent of FPL who are not receiving SSI or SSDI benefits, I calculate the average percent of employees in firms sized 1 to 24 over the years 2000 to 2011 to be 33 percent.

problem. Additionally, to address some concerns related to firm-size categories in the CPS, I check the robustness of my results to different definitions of small and large firms.

Kolstad and Kowalski (2012a) noted and verified with the Census Bureau that the individuals in Commonwealth Care (subsidized Connector coverage) and Commonwealth Choice (unsubsidized Connector coverage) were coded as Medicaid recipients in the CPS. To identify individuals in the CPS with subsidized coverage I assign observations for individuals between 133 and 300 percent of the FPL who report Medicaid coverage as receiving subsidized coverage, and individuals above 300 percent of the FPL who report Medicaid coverage as receiving unsubsidized coverage. Because my analysis focuses solely on income-eligible workers of ages 18 to 64, and because Massachusetts did not expand adult Medicaid eligibility, my analysis should capture the differences in subsidized Connector coverage take-up between small- and large-firm employees.

The Connector reported that of the approximate 42,000 individuals enrolled in Commonwealth Choice in 2011 (unsubsidized Connector coverage) at all income levels, about 4,500 are small-firm workers and their dependents (Commonwealth Health Insurance Connector Authority, 2012). From CPS data, I estimate the average subsidized coverage enrollment for employees in firm sizes 1-24 from 2000 to 2006 at 18,604 individuals per year, and from 2008 to 2011 at 53,194. This represents an average increase of 34,590 from pre- to post-period. The increase of 34,590 workers in the 133 to 300 percent of the FPL range far outweighs the total reported value of 4,500 total enrollees (workers and dependents) from all income levels in Commonwealth Choice (unsubsidized coverage). Therefore, almost all of the increase in coded Medicaid coverage in my CPS sample of interest appears to be coming from subsidized Connector coverage, of which the Connector reports a total enrollment of 192,000 in 2011.

As a robustness check, I also use CPS data corresponding to years 2003-2011 in conjunction with the Medical Expenditure Panel Survey - Insurance Component (MEPS-IC) summary tables from 2003-2006 to construct a synthetic control group to analyze the impact of the MHCI's firm-size-dependent employer mandate on coverage distributions at an aggregate level.

1.5 Identification Strategy

To identify the extent to which more lenient mandates on small firms have increased the tendency of such firms to shift their workers onto government subsidized insurance rolls, I exploit the difference in how the MHCI treats small and large firms with respect to the "fair and reasonable" contribution requirement of the employer mandate. I demonstrate that when one looks specifically at the population for which substitution of employer coverage towards subsidized coverage might occur (among workers who are income eligible for subsidies), there is evidence of substantial differences in the source of health insurance coverage by firm size. Small firms are subject to far less stringent requirements on what constitutes a "fair and reasonable" contribution to health insurance, and they are also subject to smaller penalties resulting from uninsured employees accessing services through the health safety net.

The main goal of this research is to assess the asymmetric impact of the MHCI's firm-size-dependent employer mandate on health insurance coverage distributions. The difference in the treatment of small and large firms under the MHCI generated a quasi-experiment within the state. Thus, I compare the effect of the firm-size-dependent employer mandate on small-firm employees' coverage distributions relative to large-firm employees within Massachusetts. Assuming that other states which have not implemented widespread health reform laws are a valid counterfactual for Massachusetts; I can identify the difference in the MHCI's treatment effect on small firms compared to large firms due to the different application of the employer mandate. Furthermore, working under the assumption that the treatment effect on small and large firms would be identical if both firm sizes were subject to the more stringent large-firm employer mandate, I can identify the trade-offs inherent in applying a more lenient mandate to small firms. As noted above, I expect ESI take-up to decrease and subsidized coverage take-up to increase for small-firm employees relative to large-firm employees.

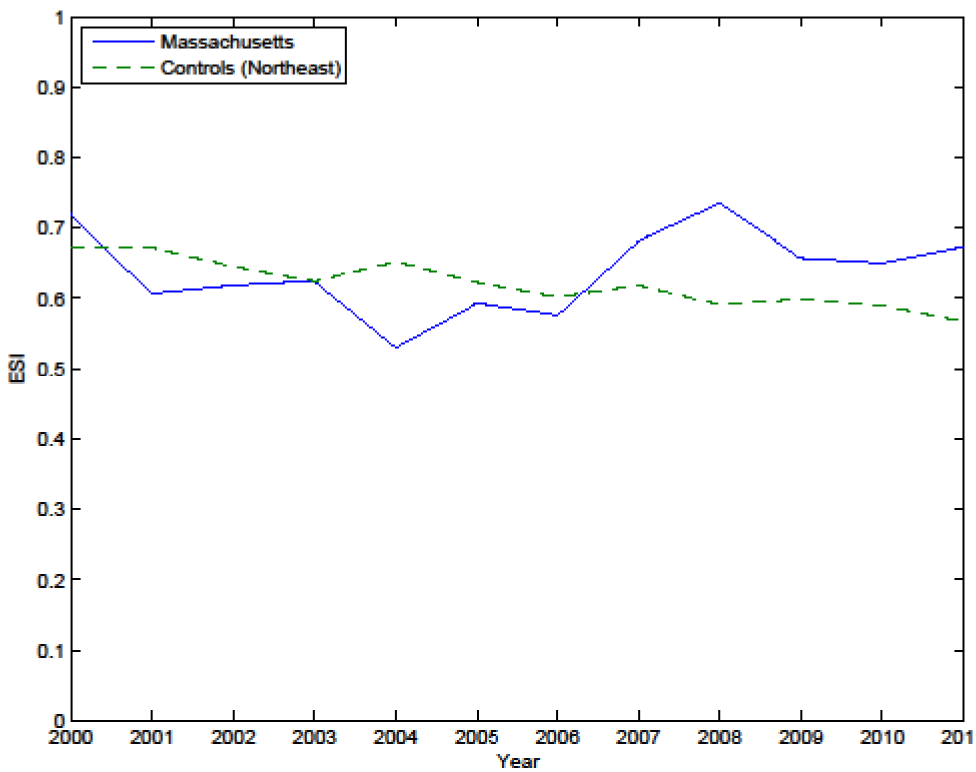
To identify the impact of the firm-size-dependent employer mandate by firm size, I first focus solely on the subsample of 18-to-64 year-old workers who are between 133 and 300 percent of the FPL, who work in the private sector, and who do not receive any SSI or SSDI benefits. Massachusetts small-firm workers in this cohort have a greater ability to overcome the firewall to access subsidies than workers in large firms. Using this sample, I estimate a triple-difference model, which allows me to compare the coverage outcomes in Massachusetts by firm size while controlling for the counterfactual situation in which Massachusetts did not implement the MHCI by using a set of reasonable control states.

1.5.1 Triple Difference

I first estimate the coverage impacts in Massachusetts using a difference-in-difference approach to verify that the income-eligible working population in Massachusetts did in fact experience increases in ESI, subsidized coverage, and overall insurance rates. I classify workers in my sample as either being enrolled in subsidized Connector coverage (coded as Medicaid recipients in the CPS), enrolled in ESI, or uninsured. I removed from my sample individuals who reported having both ESI and subsidized coverage, as well as any individual reporting a source of health insurance coverage that was not subsidized coverage or ESI (e.g., private non-group health insurance).[10] Figures 1.4, 1.5, and 1.6 display the distribution of

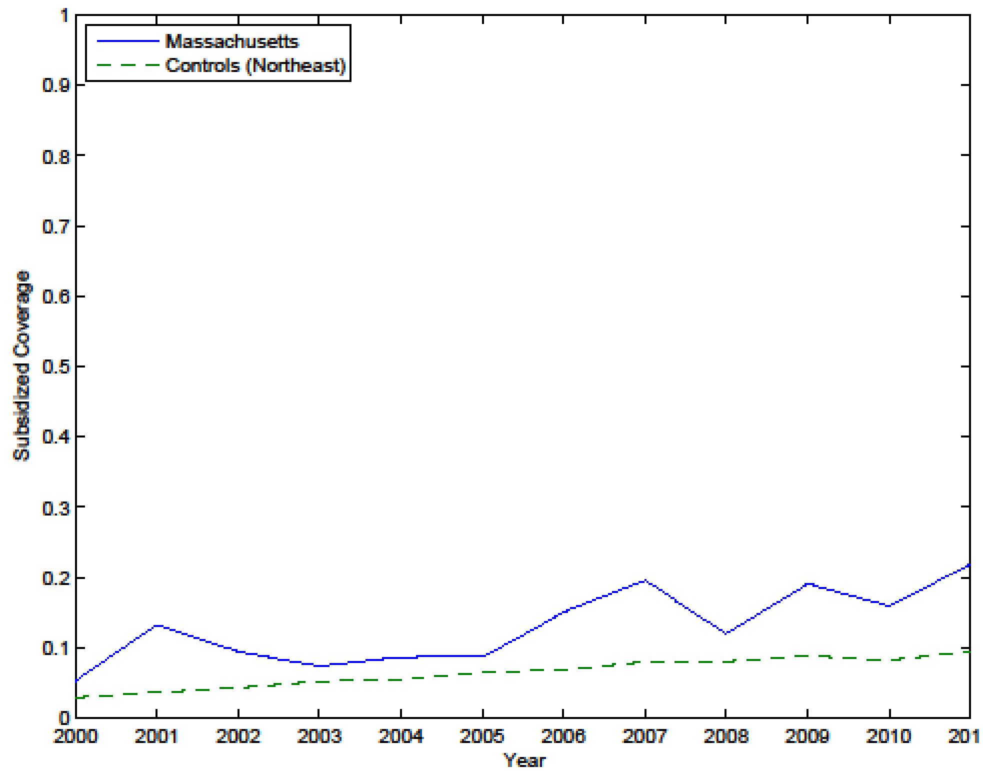
[10] This sample limitation resulted in a removal of 174 (6.69%) observations from Massachusetts and 2,564 (6.28%) observations from the main Northeast control states group.

individuals by coverage type in Massachusetts compared to the Northeast control states for the sample of 18-to-64 year-old workers who are between 133 and 300 percent of the FPL, who work in the private sector, and who do not receive any SSI or SSDI benefits. The Massachusetts reform was passed in 2006, implemented in 2007, and finalized by the beginning 2008, thus I view 2007 as a during period in which the implementation of the MHCI was completed. Figures 1.4, 1.5, and 1.6 confirm that my subsample of income-eligible workers displays the previously documented result that there is no evidence of crowd-out and that the MHCI resulted in increases in ESI, subsidized coverage, and overall insurance rates.



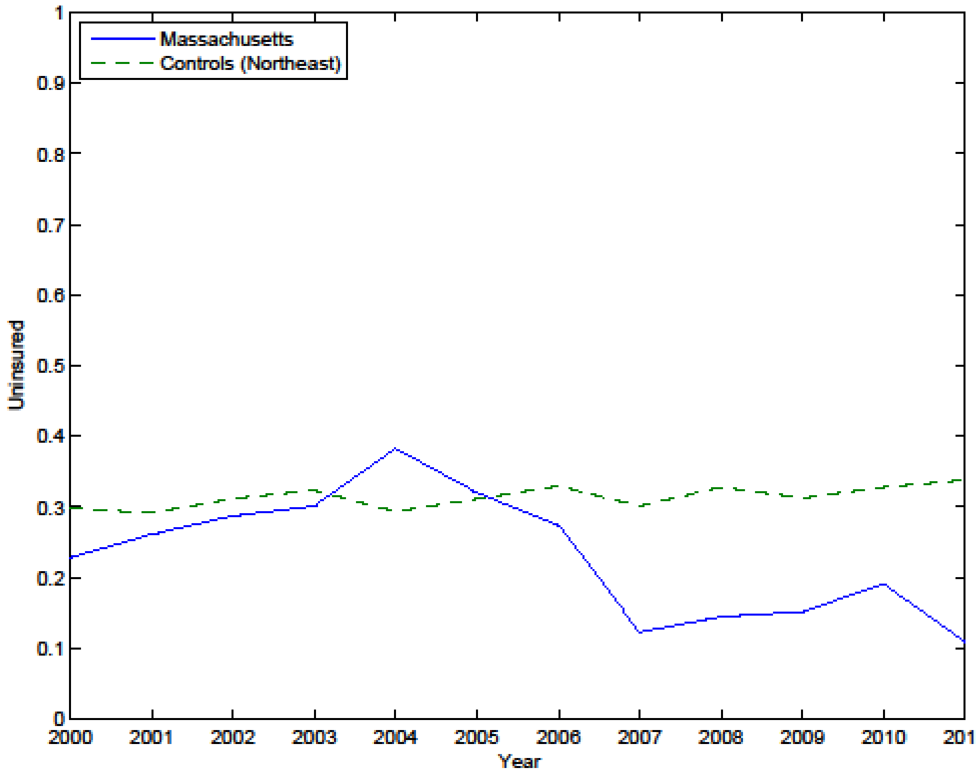
Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits.

Figure 1.4: ESI: Massachusetts vs. North East (Income-Eligible Workers)



Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits.

Figure 1.5: Subsidized Coverage: Massachusetts vs. North East (Income-Eligible Workers)



Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits.

Figure 1.6: Uninsured: Massachusetts vs. North East (Income-Eligible Workers)

Table 1.1 displays the summary statistics for insurance outcomes and predictors of insurance outcomes in Massachusetts and the Northeast control states for the pre-period (2000-2006) compared to the post-period (2008-2011) calculated from the CPS sample of income-eligible workers (the during period of 2007 has been omitted). It is important to note here that income-eligible workers in firms sized 1 to 24 comprise about one third of the total income-eligible working population in Massachusetts in all years (2000-2011). This corresponds to about 130,000 small-firm workers that are income eligible for subsidized coverage in any given year. Thus, any dissimilar impacts on coverage distributions due to the firm-size-dependent employer mandate are non-trivial in that the different treatment impacts at a minimum one third of the income-eligible working population in Massachusetts.

Table 1.1 displays the pre-period and post-period summary statistics for FPL, firm size, educational attainment, race, age, sex, and family characteristics. Neither Massachusetts nor the control states experienced any dramatic changes in the insurance predictor variables when moving from the pre-period to post-period. It is worth noting here that the more lenient treatment of small firms under the MHCIs employer mandate should result in small-firm employment growth because the MHCI reduces the short-run costs of hiring income-eligible workers by allowing them access to subsidized health insurance coverage (Gourio and Roys, 2012). I do not observe this outcome in the post-period for Massachusetts, and there are several confounding factors that may contribute to this finding. First, employment growth in the small-firm business sector requires additional investment and the creation of more small firms, which is a long-run concept. I only observe four post years, which is not nearly enough time to capture any small-firm employment growth effects. Second, the United States was in the midst of the "great recession" throughout the implementation and post-periods of the MHCI.[11] This served to dampen all employment growth, especially in the small-firm market, due to relatively limited access to liquid assets and investment for creating new firms. Thus, future research should focus on the long-run implications of the MHCI and the effect on small-business growth, as I am unable to capture this phenomenon. The regression unadjusted difference-in-difference estimates for insurance outcomes reveal an increase in both ESI and subsidized insurance, and the sum of the increase for both ESI and subsidized coverage equals

[11] I tested whether unemployment in Massachusetts responded differently to the recessions compared to the North-east control group over the following time periods: 2000-2012, 2000-2003 (minor recession), 2004-2007 (no recession), and 2008-2010 (the "great recession"). I regressed a time trend, a Massachusetts fixed effect, and an interaction term of the time trend and the Massachusetts fixed effect on annual unemployment reported by the BLS and found that unemployment trends in Massachusetts did not statistically differ from those of the Northeast control states for any of the time periods listed above.

the increase in overall insurance rates. These results are in line with past analyses of the MHCI.

Table 1.1: Summary Statistics

	North East			Massachusetts			Difference in Difference
	Pre	Post	Difference	Pre	Post	Difference	Difference in Difference
N	21,927	13,084		1,524	740		
Weighted Count	25,714,283	15,246,150		2,829,006	1,567,623		
Insurance Outcomes							
ESI	0.64	0.59	-0.05	0.61	0.68	0.06	0.12
Subsidized Coverage	0.05	0.09	0.04	0.1	0.17	0.08	0.04
Uninsured	0.31	0.33	0.02	0.29	0.15	-0.14	-0.16
Insurance Predictors							
Age	37.21	38.09	0.88	37.15	37.1	-0.04	-0.92
Male	0.51	0.52	0	0.47	0.44	-0.04	-0.04
Family Size	2.81	2.71	-0.1	2.79	2.77	-0.02	0.08
Married	0.44	0.41	-0.03	0.4	0.38	-0.02	0.01
Dependents (indicator)	0.72	0.69	-0.03	0.69	0.68	-0.01	0.02
Children (indicator)	0.48	0.44	-0.04	0.46	0.45	-0.01	0.03
Median FPL	2.24	2.26	0.01	2.24	2.29	0.04	0.03
Full Time	0.89	0.87	-0.02	0.85	0.84	-0.01	0.01
Firm Size < 10	0.18	0.18	0	0.19	0.18	-0.01	-0.02
Firm Size 10-24	0.14	0.19	0.06	0.13	0.16	0.03	-0.02
Firm Size 25-99	0.17	0.12	-0.05	0.15	0.1	-0.05	0.01
Firm Size 100-499	0.15	0.14	-0.01	0.16	0.15	-0.01	0
Firm Size 500-999	0.06	0.05	-0.01	0.06	0.07	0.01	0.02
Firm Size 1,000+	0.3	0.31	0.01	0.31	0.33	0.02	0.01
White	0.75	0.74	-0.01	0.8	0.8	-0.01	0

Table 1.1 (Continued)

Black	0.19	0.19	0	0.13	0.14	0.01	0.01
Native American	0.01	0.01	0	0.01	0	0	-0.01
Asian	0.05	0.06	0.01	0.06	0.07	0	-0.01
Hispanic	0.18	0.22	0.04	0.18	0.15	-0.03	-0.07
Less than High School	0.17	0.14	-0.03	0.19	0.1	-0.08	-0.05
High School Diploma	0.43	0.41	-0.02	0.4	0.39	0	0.01
Some College	0.26	0.27	0.02	0.25	0.29	0.04	0.02
College Graduate	0.1	0.13	0.02	0.13	0.17	0.04	0.02
Graduate School	0.03	0.04	0.01	0.04	0.04	0.01	0
At least High School	0.83	0.86	0.03	0.81	0.9	0.08	0.05
At least College	0.14	0.17	0.03	0.17	0.22	0.05	0.02

Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. All data has been weighted by the March CPS Supplement weight.

To formalize the intuition from Figures 1.1, 1.2, and 1.3 and Table 1.1, I estimate the following difference-in-difference model (equation 1.1):

$$y_i = \alpha + \beta(MA * Post)_i + \gamma(MA * During)_i + X_i'\delta + \sum_s \phi_s + \sum_t \tau_t + \varepsilon_i$$

I include a during period for 2007 and a treatment period for 2008 to 2011.[12] The identification assumption used for the estimation of equation 1.1 is that aside from the Massachusetts reform, no other factors differentially impacted the coverage outcome variables between Massachusetts and the control states. I estimated equation 1.1 for all three coverage outcomes (ESI, subsidized coverage, uninsurance) jointly using seemingly unrelated regression estimation. Each observation corresponds to a person *i* in state *s* at time *t*. β is the difference-in-difference coefficient of interest. The matrix X_i includes individual and family characteristics[13], and ϕ_s and τ_t are state- and year- fixed effects, respectively; thus the difference-in-difference estimate is identifying changes within Massachusetts over time. The standard errors from this regression are clustered at the state level.

Table 1.2 displays regression coefficients from the estimation of equation 1.1. The estimates of the parameters of interest (β) are all significant at the 1-percent level. These estimates indicate an increase in both ESI and subsidized coverage in Massachusetts, and the sum of the coefficients from the ESI and subsidized coverage equations equals the increase in overall insurance rates.

---

[12] Kolstad and Kowalski (2012a) also account for a during period in 2007 for their difference-in-difference analysis of coverage distributions.

[13] The characteristics are age category, FPL category, sex, family size, marital status, full-time vs. part-time employee, presence of dependents, race, ethnicity, firm size, and education.

Table 1.2: Difference in Difference Estimation (N=40,696)

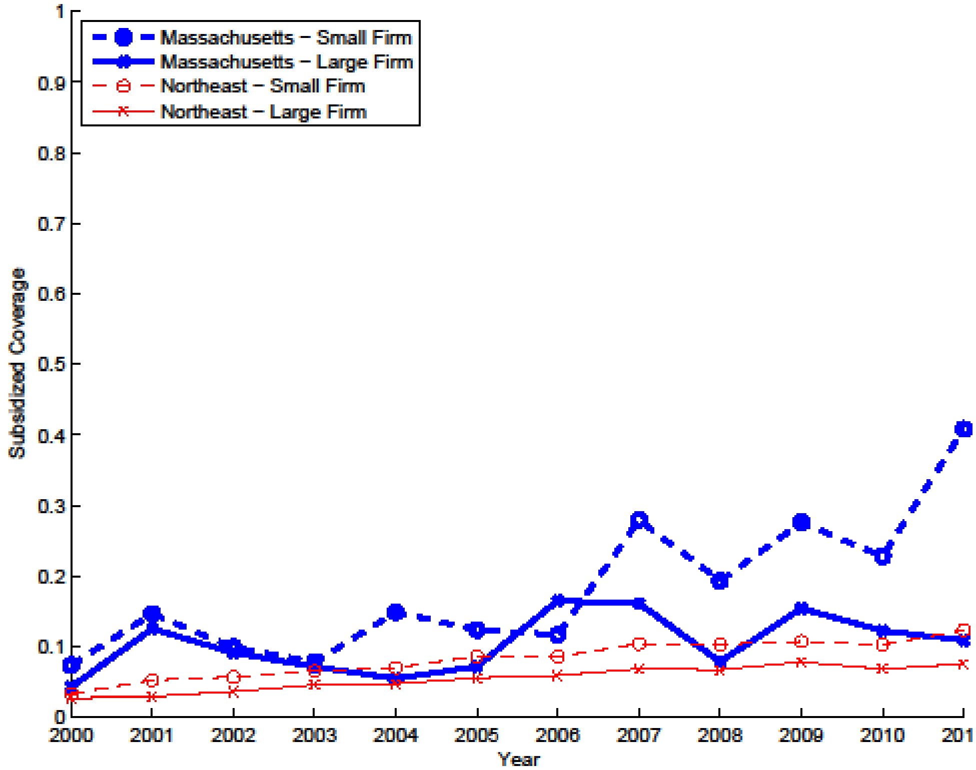
Variable	ESI	Subsidized Coverage	Uninsured
MA * Post	0.088	0.044	-0.132
	(0.005)***	(0.006)***	(0.010)***
MA * During	0.091	0.079	-0.17
	(0.009)***	(0.009)***	(0.016)***
Demographic Characteristics	Y	Y	Y
State Fixed Effects	Y	Y	Y
Year Fixed Effects	Y	Y	Y

Notes: The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. Standard errors are clustered at the state level. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

This difference-in-difference estimation for income-eligible workers matches previous research that has used difference-in-difference techniques to analyze changes in the insurance coverage distribution for all Massachusetts residents due to the MHCI. The next step is to focus on the different treatment effects of a firm-size-dependent employer mandate in Massachusetts. Figures 1.7, 1.8, and 1.9 display the trends in insurance outcomes in Massachusetts and the Northeast control states by firm size (1-24 vs. 25+) for the sample of workers of ages 18 to 64 who are between 133 and 300 percent of the FPL and who work in the private sector but do not receive any SSI or SSDI benefits. During the pre-period (2000-2006), large-firm employees were more likely to have ESI than small-firm employees, but small and large firms in Massachusetts move together. The same holds true for ESI in the Northeast control states. Large-firm workers were also more likely to be insured in the pre-period and about equally likely to have public coverage compared to small-firm workers. Additionally, the general trends for subsidized coverage and uninsurance rates for the pre-period match reasonably well. It is important to note here that uninsurance rates for workers between 133 and 300 percent of the FPL in Massachusetts are between 10 and 25 percent post-reform. This is relatively high compared to the overall uninsurance rate of 2 percent, thus lower-income workers in Massachusetts are far more likely than the overall population to lack health insurance coverage.

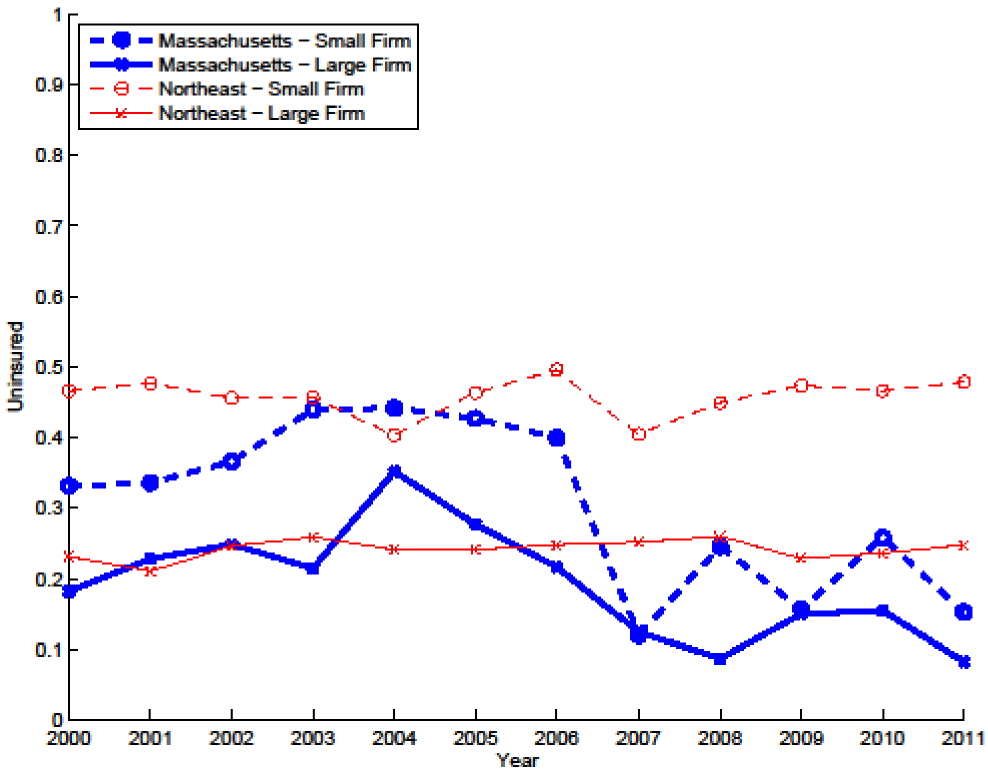
Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. Small firms are defined as 1-24 employees and large firms as 25 or more employees.

Figure 1.7: ESI: Massachusetts vs. North East



Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. Small firms are defined as 1-24 employees and large firms as 25 or more employees.

Figure 1.8: Subsidized Coverage: Massachusetts vs. North East



Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. Small firms are defined as 1-24 employees and large firms as 25 or more employees.

Figure 1.9: Uninsured: Massachusetts vs. North East

Table 1.3 displays the summary statistics for insurance outcomes and the predictors of insurance outcomes (FPL, firm size, educational attainment, race, age, sex, and family characteristics) by firm size in Massachusetts and in the Northeast control states for the pre-period (2000-2006) compared to the post-period (2008-2011) calculated from the CPS sample of income-eligible workers (the during period of 2007 has been omitted). Neither Massachusetts nor the control states show any dramatic changes in these predictor variables. The regression unadjusted triple-difference estimates for insurance outcomes can be used to construct an estimate of small-firm ESI to subsidized insurance coverage shifts. I use the following definition (equation 1.2) for small-firm coverage shifts: Let β_{ESI} and $\beta_{Subsidy}$ be the triple-difference estimates for ESI and subsidized coverage, respectively.

$$Coverage\ Shift = -\frac{\beta_{ESI}}{\beta_{Subsidy}}$$

This definition can be interpreted to mean that for all individuals in small firms who are newly covered by subsidized coverage, the fraction Coverage Shift would have chosen ESI had they been subject to the more stringent large-firm employer mandate. Using equation 1.2 and the estimates provided in Table 1.3, the estimated coverage shift is 40 percent and the different impact on overall insurance rates for workers in small firms is 7 percent. This can be interpreted to mean that 40 percent of small-firm workers newly covered by subsidized insurance would have taken up ESI had they been subject to the more stringent large-firm employer mandate. And the trade-off of applying the more stringent large-firm mandate to all firms would be an observed decrease of 7 percent in overall insurance rates for small-firm workers.

Table 1.3: Summary Statistics by Firm Size

	Control States				Massachusetts				Triple
	Pre-LF	Pre-SF	Post-LF	Post-SF	Pre-LF	Pre-SF	Post-LF	Post-SF	Difference
N	15,157	6,770	8,410	4,674	1,022	502	488	252	
Weighted Count	17,626,284	8,087,999	9,541,953	5,704,196	1,915,560	913,446	1,029,789	537,835	
Insurance Outcomes									
ESI	0.72	0.48	0.68	0.42	0.67	0.50	0.76	0.52	-0.05
Subsidized Coverage	0.04	0.07	0.07	0.11	0.09	0.11	0.12	0.28	0.12
Uninsured	0.24	0.46	0.24	0.47	0.25	0.39	0.12	0.20	-0.07
Insurance Predictors									
Age	37.27	37.09	38.16	37.98	36.83	37.82	37.36	36.60	-1.75
Male	0.49	0.56	0.49	0.57	0.46	0.51	0.43	0.44	-0.06
Family Size	2.81	2.80	2.72	2.69	2.79	2.79	2.73	2.84	0.14
Married	0.43	0.45	0.39	0.44	0.38	0.44	0.35	0.44	0.01
Dependents (indicator)	0.72	0.71	0.69	0.69	0.69	0.69	0.67	0.72	0.04
Children (indicator)	0.50	0.44	0.46	0.41	0.45	0.48	0.43	0.49	0.02
Median FPL	2.26	2.18	2.27	2.22	2.29	2.16	2.26	2.31	0.14
Full Time	0.90	0.86	0.87	0.86	0.86	0.81	0.84	0.83	0.02
Firm Size < 10	0.00	0.57	0.00	0.49	0.00	0.59	0.00	0.53	0.01
Firm Size 10-24	0.00	0.43	0.00	0.51	0.00	0.41	0.00	0.47	-0.01
Firm Size 25-99	0.25	0.00	0.19	0.00	0.22	0.00	0.16	0.00	0.01
Firm Size 100-499	0.23	0.00	0.23	0.00	0.23	0.00	0.22	0.00	0.01
Firm Size 500-999	0.09	0.00	0.09	0.00	0.09	0.00	0.11	0.00	-0.03
Firm Size 1,000+	0.43	0.00	0.49	0.00	0.46	0.00	0.51	0.00	0.01
White	0.73	0.79	0.72	0.76	0.78	0.86	0.79	0.82	-0.03
Black	0.22	0.13	0.22	0.14	0.15	0.08	0.15	0.10	0.02
Native American	0.01	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.00

Table 1.3 (Continued)

Asian	0.05	0.07	0.05	0.09	0.07	0.05	0.06	0.07	0.01
Hispanic	0.16	0.23	0.18	0.30	0.18	0.19	0.15	0.16	-0.06
Less than High School	0.15	0.23	0.11	0.19	0.18	0.21	0.11	0.08	-0.07
High School Diploma	0.44	0.43	0.41	0.42	0.37	0.45	0.35	0.47	0.02
Some College	0.27	0.23	0.29	0.24	0.27	0.22	0.29	0.29	0.07
College Graduate	0.11	0.09	0.14	0.11	0.14	0.10	0.20	0.13	-0.02
Graduate School	0.03	0.03	0.04	0.03	0.04	0.03	0.05	0.03	-0.01
At least High School	0.85	0.77	0.89	0.81	0.82	0.79	0.89	0.92	0.07
At least College	0.14	0.12	0.18	0.15	0.19	0.12	0.25	0.15	-0.02

Notes: CPS data. The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. Small firms (SF) are defined as 1-24 employees and large firms (LF) as 25 or more employees. All data has been weighted by the March CPS Supplement weight.

To formalize the intuition from Figures 1.7, 1.8, and 1.9 and Table 1.3, I estimate the following equation (equation 1.3) for all three coverage outcomes (ESI, subsidized coverage, uninsurance) jointly using a seemingly unrelated regression estimation:

$$
\begin{aligned}
y_i = \alpha + \beta(MA * Post * Small\ Firm)_i + \gamma_1(MA * During * Small\ Firm)_i \\
+ \gamma_2(MA * Post)_i + \gamma_3(MA * During)_i \\
+ \sum_s \phi_s(Small\ Firm)_i \\
+ \sum_t \tau_t(Small\ Firm)_i + X_i'\delta + \sum_s \phi_s + \sum_t \tau_t + \varepsilon_i
\end{aligned}
$$

Each observation corresponds to a person *i* in state *s* at time *t*. β is the triple-difference coefficient of interest. The matrix X_i includes individual and family characteristics[14], and ϕ_s and τ_t are state- and year-fixed effects, respectively. Thus, the parameter of interest (β) is identified from the variation between small firms and large firms in Massachusetts from the pre-period to the post-period. The standard errors from this regression are clustered at the state level.

The identifying assumption for this triple-difference estimation strategy is that outside of the Massachusetts reform and the different application of the employer mandate by firm size, no other factors differentially impacted the coverage outcome variables between Massachusetts and the control states and small firms and large firms. Additionally, to explicitly state the trade-offs of applying a firm-size-dependent employer mandate in Massachusetts I must assume that the treatment effect of the MHCI would have been identical for both small and large firms had both firm sizes been subject to the same employer mandate. Specifically,

[14] The characteristics used are the same as the difference-in-difference estimation (excluding firm size less than 25).

outside of the different application of the employer mandate, no other factors differentially impacted the coverage outcome variables between small and large firms in Massachusetts.

1.6 Robustness Checks

1.6.1 Overview

The first threat to my identification strategy is that the employer fine for non-compliance is relatively low: it is set at $295 per FTE per year. Thus, it may be reasonable to assume that both large and small firms would restructure their employment contracts to allow their income-eligible employees to choose between accessing subsidies and the firm's ESI plan while paying a seemingly trivial fine. If this were true then the assumption that small-firm employees can overcome the categorical firewall to access subsidies more easily than large-firm employees does not hold, and the differences in coverage distributions would be generated by some other factor outside of the different application of the employer mandate.

Another issue that to address is whether or not small-firms have increased the ESI premium share that their employees must pay. If small firms have not allowed their income eligible employees to be categorically eligible for subsidies by increasing their premium contribution share then the mechanism through which differences in coverage distributions exist due to special treatment of small-firms under the employer mandate does not hold.

Absent any spillover effects across state lines, the assumption that no other factors outside of the MHCI affected coverage distributions between Massachusetts and the control states should hold in general. The MHCI only affected the residents of Massachusetts and no other states. A spillover effect that would pose a threat to my identification is migration of lower-income small-firm workers from neighboring states into Massachusetts. I argue in more detail below that lower-income small-firm worker migration would produce an overestimate of small-firm ESI to subsidized insurance coverage shifts.

Another threat to my identification strategy would be the existence of an adjustment period in Massachusetts over which firms and employees had a slow reaction to the incentives embedded in the MHCI. This phenomena could dampen all estimated effects toward zero, but also might initially bias ESI estimates upwards. Suppose firms and workers responded to the MHCI by initially offering and taking up ESI respectively, then small firms learned that they could reduce labor costs by changing their ESI contracts to allow their income-eligible workers access to subsidies. This behavior would result in large initial increases in ESI rates for small firms that eventually decrease over the small-firm learning process. Additionally, there would be relatively low take-up of subsidized coverage throughout the learning process. This would initially result in increased ESI and overall insurance rates followed by decreased in ESI and increases in subsidized coverage rates. The learning process would result in different post-period trends that ultimately serve to bias estimates of small-firm ESI to subsidized insurance coverage shifts downward.

The MHCI generates a larger incentive for lower-income workers to take up subsidized coverage due to the higher subsidies awarded to lower-income workers. This is not necessarily a threat to identification, but it is an issue worth investigating to verify that heterogeneity exists in the treatment effect by FPL. Additionally, the assumption that small and large firms in the control states can serve as counterfactuals for Massachusetts small and large firms requires small and large firms in Massachusetts to react to economic conditions with respect to ESI offerings similarly. States have different regulations with regard to insurance markets, thus ESI offerings may be differentially affected by the same economic conditions across states. For example, community rating and guaranteed issue in health insurance markets raises the cost of insurance relative to states that have not imposed guaranteed issue and community rating. Massachusetts implemented community rating and guaranteed issue in 1996, therefore Massachusetts firms may respond differently to economic conditions when choosing ESI plans to offer their employees.

Below in sections 1.6.2-1.6.10, I address each of the potential threats to my primary estimations. I then provide robustness checks in the results section that follows.

1.6.2 Small Employer Fines

The relative ease with which small-firm employees can overcome the categorical firewall to access subsidized coverage hinges upon the employer fine ($295 per FTE per year) being large enough to cause a differential response between small and large firms. The decision of a firm sized 11 to 50 FTE employees to allow their income eligible employees to have the option of choosing either subsidized coverage or the firm's ESI plan imposes no additional fines on the employer since they are in compliance with the "fair and reasonable" contribution requirement. While a large firm must weigh the costs of a $295 per FTE per year fine against the potential savings from allowing their income eligible workers access to subsidized coverage. Therefore, the ultimate decision of a large firm to not be in compliance with the "fair and reasonable" contribution requirement to allow their income eligible employees access to subsidies depends entirely upon the distribution of incomes within the firm.

Suppose a that a small firm with 40 FTEs and 30 full-time employees is deciding whether to allow their income-eligible employees the option to choose either subsidized coverage or the firm's ESI plan. If 8 full-time employees are above 300 percent of the FPL and enrolled in ESI then the firm meets the "fair and reasonable contribution" requirement and can allow the other 22 employees below 300 percent of the FPL to access subsidies without facing any employer fines if the employer pays less than 33 percent of the single premium. If the employer was contributing more than 33 percent of the annual premium prior to this decision, the employer would simply pass back the increased employee contribution in wages to make the employee no worse off economically, independent of the employee's ultimate coverage choice.

Now suppose that a large firm with 300 FTEs and 150 full-time employees is considering the same problem. If 125 full-time employees are above 300 percent of the FPL and the employer pays less than 33 percent of the single premium, then the 25 income-eligible full-time employees can access subsidies, but the firm is fined $88,500 (300295). This amounts to an average fine of $3, 540 per subsidized coverage enrollee. If the firm does not save at least $3,540 per subsidized coverage enrollee then it will not violate the "fair and reasonable contribution" requirement. This stylized calculation also assumes that all income-eligible employees would choose to enroll in subsidized coverage. If this is not the case then the per-subsidized-coverage enrollee fine increases.

Therefore there may be instances in which large firms find it beneficial to pay the $295 per FTE per year fine to allow their income-eligible employees to access subsidized coverage, but there are also instances in which it is not in the firm's interest to engage in such behavior. My assumption that the employer fine generates asymmetric behavioral responses across small and large firms is appropriate if the fine is large enough such that some large firms choose not to allow their income-eligible employees to access subsidized coverage. I do not need to assume anything about the distribution of employees within a firm, only that there are instances in which large firms do not allow their income-eligible employees to access subsidized coverage in order to avoid the fine and be in compliance with the mandate.

1.6.3 Premium Share

The mechanism through which small-firms can allow their income eligible employees to access subsidized coverage without creating any economic harm to all of their employees while avoiding the $295 per FTE fine relies on the assumption that employers have increased the share of the ESI premium that their employees must pay. I do not have micro-data that allows me to fully address whether or not employers have increased ESI employee contribution shares, but there is indirect evidence that this behavior is in fact occurring.

The MEPS-IC summary tables and the Blue Cross Blue Shield of Massachusetts (2012) report present evidence that small firms are in fact requiring their employees to pay a higher fraction of their health insurance premiums post-MHCI reform. The Blue Cross Blue Shield of Massachusetts (2012) report claims that all employers have decreased their contributions toward ESI subsequent to the implementation of the MHCI. In addition, the MEPS-IC summary tables reveal that small firms (firms of fewer than 50 employees) have, on average, increased the premium share that employees must contribute to their single-coverage health plans by almost 6 percentage points more than large firms in Massachusetts subsequent to MHCI implementation (2000-2006 vs. 2008-2011).[15] This 6 percent premium share increase in Massachusetts small firms corresponds to more than an 8000 percent increase in premium shares compared to national averages. Additionally, the Massachusetts Division of Health Care, Finance, and Policy (2013) report notes that in 2011 93.9 percent of all firms with more than 11 FTEs offered a section 125 plan while 93 percent of firms sized 11 to 25 FTEs and 96 percent of firms sized 26 or more FTEs were in compliance with the "fair and reasonable" contribution requirement. Therefore, almost all non-exempt firms offered health insurance (93.9 percent) and almost 100 percent of offering firms were in compliance with the "fair and reasonable" contribution. Therefore any large differences in subsidized coverage take-up

[15] This is a regression unadjusted triple-difference estimate comparing Massachusetts small- and large-firms before and after the MHCI reform to the national average for small- and large-firms.

between small and large firms should be driven by mandate-compliant small-firms allowing their income-eligible employees to access subsidies by increasing the employee ESI premium share.

1.6.4 Firm Size Definition

I cannot capture firms sized 1 to 50; hence I used firms sized 1 to 24 compared to firms over 25 for my main estimation. I check the robustness of my results by estimating equation 1.3 for varying definitions of small firms and large firms. Table 1.4 displays the alternative definitions of small and large firms.

1.6.5 Implementation of Less Substantial Health Reforms

Over the analysis period California, Maine, Vermont, and Oregon implemented less substantial health reforms, which may serve to bias all of my estimates toward zero. To address this issue I re-estimate equation 1.3 using my original Northeast control states, with Maine and Vermont excluded. Additionally, I estimate equation 1.3 for the contiguous 48 states and the contiguous 48 states with California, Maine, Vermont, and Oregon removed as well. The additional control group of the 48 contiguous states serves as a robustness check to my Northeast control group specification. ESI has been the traditional source of health insurance for workers since World War II, thus firms in all states have adapted to this market feature over the past 70 years. Across-state trends in ESI for the 48 contiguous states should be relatively similar due to the tenure of ESI as a market institution. Estimates from the Northeast and the contiguous 48 states should be nearly identical.

Additionally, the inclusion of the 48 contiguous states as a control group allows me to effectively use a non-parametric block bootstrap t technique to assess the significance of my estimates. Block bootstrapping a distribution of t-statistics that include the cluster robust variance estimator as an asymptotic refinement has been shown to be successful in correcting for the underestimation of the standard deviation of the estimates in difference-in-difference estimation (Bertrand et al., 2004; Cameron et al., 2008). I include significance estimates from a block bootstrap t-statistic procedure for the baseline firm-size definition with a 48 contiguous states control group using 10,000 sample draws. I use the block bootstrap procedure over other methods (e.g., wild bootstrap methods) due to a significant reduction in power of the bootstrap test when using alternative methods (Cameron et al., 2008).

1.6.6 Heterogeneous Insurance Market Regulations

To test whether heterogeneous insurance market regulations across Massachusetts and the control states bias my estimates, I re-estimate equation 1.3 including only New Jersey, New York, and Washington as control states. These three states and Massachusetts all implemented guaranteed issue and community rating prior to 1997 and still have these policies in place as of 2013.[16]

1.6.7 Migration Spillovers

Migration of the uninsured small-firm population from other New England states into Massachusetts would increase the percentage of small-firm workers in Massachusetts on the subsidized health coverage rolls, have no effect on neighboring states small-firm employee subsidized coverage take-up (subsidized coverage is not an option for workers living outside Massachusetts), decrease the percent of small-firm workers with ESI in Massachusetts (adding more subsidized coverage enrollees to Massachusetts decreases the percent with ESI), increase the percentage of ESI coverage in neighboring states (removal of uninsured persons from the

[16] Massachusetts implemented these policies in 1996, New Jersey in 1992, New York in 1993, and Washington in 1993.

population increases the percent already in the state with ESI), and decrease the overall percentage of uninsured workers in both Massachusetts and its neighboring states. The combined effect of small-firm worker migration would bias the ESI triple-difference estimate downward due to biasing the treatment effect of the MHCI on small firms toward zero, bias the subsidized coverage triple-difference estimate upward, and have an ambiguous effect on the uninsurance triple-difference estimate. It is more likely that the negative bias on the ESI triple-difference estimate will outweigh the positive bias on the subsidized coverage estimate due to the bias on the MHCI small-firm treatment effect toward zero while maintaining a large and positive treatment effect for ESI coverage rates in large firms. Therefore, these biases would combine to produce an overestimate of small-firm ESI to subsidized insurance coverage shifts.

To address the potential occurrence of migration spillovers, I re-estimate equation 1.3 using the surrounding New England states of Maine, Vermont, New Hampshire, Connecticut, and Rhode Island, as well as the surrounding New England states with Maine and Vermont removed due to their implementation of less substantial health reforms during the analysis period. If spillovers exist, I would expect a negative bias on the triple-difference estimate for ESI and a positive bias on the triple-difference estimate for subsidized coverage. These biases, arguably, would result in an overestimate of small-firm ESI to subsidized insurance coverage shifts. Subsequent to this test, I also re-estimate equation 1.3 using my original Northeast control group with the above listed New England states removed. I additionally estimate equation 1.3 for the contiguous 48 states with the New England states removed, and again with the New England states along with California and Oregon removed.

1.6.8 Heterogeneity in the Treatment Effect by FPL

I check for heterogeneity in the treatment effect by FPL by estimating equation 1.3 for FPL brackets 133 to 200 percent and 200 to 300 percent of the FPL. Due to the availability of higher subsidies for lower-income workers, I expect the treatment effect to be greater for workers in the 133 to 200 percent of the FPL bracket compared to workers in the 200 to 300 percent of the FPL bracket. Additionally I conduct a falsification test by estimating equation 1.3 for workers above 300 percent of the FPL. Employees who are not income eligible for subsidies (FPL greater than 300 percent) should not demonstrate any substantial increase in subsidized coverage. Almost all large forms offer ESI (99 percent), and just over half of small firms offer ESI (54 percent). Thus, uninsured large-firm workers have chosen to remain without coverage due to some other factor than access to ESI, while small-firm workers may be uninsured because they do not have access to insurance through their employer. The distribution of firms offering coverage by firm size indicates that increases in ESI rates due to the MHCI for large-firm workers will mostly come from uninsured employees taking up ESI that had already been offered as a result of the individual mandate, while increases in ESI rates for small-firm workers will come from increased offer rates due to the employer mandate and the individual mandate incentive to obtain health insurance as well. Therefore, small-firm workers above 300 percent of the FPL should exhibit a much larger positive increase in ESI rates due to the MHCI relative to large-firm employees.

1.6.9 Adjustment Period

To test for an adjustment period, I examine differences in pre-treatment trends and post-treatment effects by further refining my definition of pre-periods and post-periods into “early pre-period” (2000-2003), “late pre-period” (2004-2006), “during” (2007), “early post-period” (2008- 2009), and “late post-period” (2010-2011) and estimating the following equation (equation 1.4):

$$
\begin{aligned}
y_i = \alpha + {} & \beta_1(MA * Early\ Pre * Small\ Firm)_i + \beta_2(MA * Duing * Small\ Firm)_i \\
& + \beta_3(MA * Early\ Post * Small\ Firm)_i \\
& + \beta_4(MA * Late\ Post * Small\ Firm)_i + \gamma_1(MA * Post)_i \\
& + \gamma_2(MA * During)_i \\
& + \sum_s \phi_s(Small\ Firm)_i \\
& + \sum_t \tau_t(Small\ Firm)_i + X_i'\delta + \sum_s \phi_s + \sum_t \tau_t + \varepsilon_i
\end{aligned}
$$

Larger (in absolute value) significant subsidized insurance and ESI estimates of the triple-difference parameter for the “late post-period” relative to the “early post-period” would be indicative of an adjustment period immediately following MHCI implementation.

1.6.10 Synthetic Control Group

I constructed a synthetic control group for Massachusetts small firms and large firms from aggregate data using the method outlined in Abadie et al. (2010). This method provides a robustness check to my triple-difference specification by using aggregate data and a data-driven method to develop estimates of the MHCI’s dissimilar impact on coverage distributions by firm size.

To estimate the impact on coverage distributions from the MHCI’s firm-size-dependent employer mandate using the synthetic control approach, I allow for 48 donor states: all states in the contiguous Unites States, including Washington, DC. The CPS data is aggregated up to the state-year level, and statistics from the MEPS-IC are reported in this format as well. The goal of this exercise is to generate a linear combination of donor-state insurance outcomes and insurance predictors that best match Massachusetts. To do this I solve for both W and **V** in the following equation (equation 1.5) for each insurance outcome by firm size:

$$\min_{W}(Y_{MA} - \boldsymbol{Y}W)\boldsymbol{V}(Y_{MA} - \boldsymbol{Y}W)\ s.t. W = [w_1\ w_2 \dots w_{48}]', \sum w_i = 1\ , w_i \geq 0\ \forall\ i = 1, \dots, 48$$

Y_{MA} is a column vector containing the relevant outcome variable for 2003 to 2006 (ESI, subsidized coverage, and uninsurance) and the following predictors of aggregate insurance status: average of the median FPL for workers in the 133-300 percent of the FPL range by firm size over 2003-2006, average of the fraction of college-educated workers in the 133-300 percent of the FPL range by firm size from 2003-2006, average of the fraction of firms that offered health insurance by firm size from 2003-2006, average of the fraction of employees in firms that offered health insurance by firm size from 2003-2006, and average of the fraction of employees eligible for employer-sponsored health insurance in firms that offer health insurance by firm size from 2003-2006. The aggregate coverage outcomes, median FPL, and fraction of workers who were college educated were calculated using the CPS sample previously described. The MEPS-IC tables by state and firm size were used to obtain the fraction of employers offering coverage, fraction of employees in firms that offer coverage, and fraction of employees in firms that offer coverage who are eligible to enroll in coverage.[17] $\boldsymbol{Y}$ is a matrix that has columns for each donor state corresponding to the row entries in Y_{MA}. W is a set of weights to be estimated that minimizes the distance defined in equation 1.5. $\boldsymbol{V}$ is a weighting matrix that is calculated to minimize the difference between the trajectories of the outcome variable over the 2003 to 2006 period.[18]

After estimating W I construct the synthetic control groups for Massachusetts by firm size and calculate the triple-difference average treatment effect from 2008-2011. I then estimate placebo treatment effects for each of the 48 states in the donor pool and estimate an empirical

[17] The MEPS-IC tables divided firm size by 1-50 employees and 51 or more employees.
[18] The results presented from this method are robust to using a weighting matrix that minimizes the mean squared error.

and kernel-smoothed distribution of outcomes, both which can be used to generate a measure of significance by comparing the treatment effect in MA to the placebo donor states. I then estimate the small-firm ESI to subsidized insurance coverage shifts using the calculated average treatment effects and equation 1.2.

One of the main concerns regarding the synthetic control group approach is that the researcher has a large degree of latitude in choosing the predictor variables that enter into the objective function in equation 1.5. I address this issue by re-estimating the weights from equation 1.5, including a variable containing the number of letters in the state's name (e.g., Massachusetts has 13 letters). The inclusion of this variable should not be related to coverage outcomes, thus its presence should not significantly alter the original estimation results.

1.7 Results

I summarize alternative firm-size definitions and control groups in Tables 1.4 and 1.5, respectively. Table 1.6 displays regression coefficients for the parameter of interest β on $(MA * Post * Small\ Firm)_i$ derived from the estimation of equation 1.3 for the baseline control group (the Northeast states) and for the baseline definition of firm size, as well as for the six other firm-size definitions listed in Table 1.4.

Table 1.4: Alternative Firm Size Definitions

Label	Firm Size	Label	Firm Size
SF Baseline	1-24	LF Baseline	25+
SF-1	1-24	LF-1	100+
SF-2	11-24	LF-2	100+
SF-3	11-24	LF31	25+
SF-4	1-10	LF-4	11-24
SF-5	1-10	LF-5	25+
SF-6	1-10	LF-6	100+

Table 1.5: Alternative Control Groups

Label	States
North East and Contiguous 48	
North East (Baseline)	CT, DC, DE, MD, ME, NH, NJ, NY, PA, RI, VT
Contiguous 48	The contiguous 48 state of the U.S.
Less Substantial Health Reforms	
North East Limited	CT, DC, DE, MD, NH, NJ, NY, PA, RI
Contiguous 48 Limited	The contiguous 48 state of the U.S. with CA, ME, VT, and OR removed
Community Rating and Guaranteed Issue	
Community Rating/Guaranteed Issue	NY, NJ and WA
Migration Spillovers	
New England	CT, ME, NH, RI, VT
New England Limited	CT, NH, RI
North East with New England Removed	DC, DE, MD, NJ, NY, PA
Contiguous 48 with New England Removed	The contiguous 48 state of the U.S. with CT, ME, NH, RI, and VT removed
Contiguous 48 with New England Removed Limited	The contiguous 48 state of the U.S. with CT, ME, NH, RI, VT, CA and OR removed

The first three alternative firm-size definitions (SF-1, SF-2, and SF-3) check the robustness of my baseline result to varying definitions of firm size. The small firm ESI to subsidized insurance coverage shift estimates remain highly significant and large for the baseline firm-size definition as well as for the first three alternative definitions. The last three alternative definitions test the existence of coverage shifts between mandate exempt firms (size 1-10) and other sized firms. SF-4 tests whether there are significant small-firm ESI to subsidized insurance coverage shifts between exempt firms and small firms subject to the mandate (size 11-24). This test results in a positive but not significant coverage shift estimate, indicating that there is no significant difference in the treatment effect between these two firm sizes. This result is due to an imprecise measure of the ESI triple-difference parameter. The sign of the estimate is in line with the intuition that exempt firms would rely more heavily on the Connector to provide insurance to their employees than non- exempt firms would, but the small sample sizes of these two firm-size groups and the relatively small coefficient estimate of the triple-difference parameter resulted in an imprecise estimate. A comparison of the estimates from the SF-3 and SF-5 rows provides additional evidence that exempt firms display more ESI to subsidized coverage shift than small non-exempt firms. SF-5 and SF-6 tested exempt firms against firms sized 25 and over and firms sized 100 and over respectively. Both tests resulted in positive and significant small firm ESI to subsidized insurance coverage shift estimates.

Table 1.6: Triple-Difference Estimation – Firm Size Robust

Firm Size	N	ESI	Subsidized Coverage	Uninsured	Coverage Shift
Baseline	40,696	-0.059	0.116	-0.057	0.507
(1-24 vs. 25+)		(0.021)**	(0.010)***	(0.016)***	(0.154)***
SF-1	34,271	-0.051	0.110	-0.059	0.465
(1-24 vs. 100+)		(0.021)*	(0.012)***	(0.015)***	(0.157)***
SF-2	27,048	-0.040	0.072	-0.032	0.554
(11-24 vs. 100+)		(0.020)	(0.012)***	(0.013)*	(0.219)**
SF-3	33,473	-0.049	0.078	-0.029	0.625
(11-24 vs. 25+)		(0.021)*	(0.010)***	(0.015)*	(0.212)***
SF-4	13,266	-0.025	0.079	-0.055	0.314
(1-10 vs. 11-24)		(0.018)	(0.007)***	(0.013)***	(0.209)
SF-5	34,653	-0.067	0.154	-0.088	0.432
(1-10 vs. 25+)		(0.022)**	(0.012)***	(0.018)***	(0.128)***
SF-6	28,228	-0.059	0.148	-0.089	0.398
(1-10 vs. 100+)		(0.023)**	(0.014)***	(0.017)***	(0.132)***

Notes: The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. The control group used here is the North East. Standard errors for coefficients are clustered at the state level. Standard errors for the coverage shift estimates were calculated using the delta method. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

The first three estimates (baseline, SF-1, and SF-2) demonstrate very similar effects of the MHCI on ESI, subsidized coverage and overall insurance rates. In all instances small firms responded with a lower increase in ESI rates, and with higher increases in both subsidized coverage and overall insurance rates. These responses resulted in coverage shift estimates between 46 and 55 percent. The estimates indicate that about half of newly covered small firm employees with subsidies would have chosen ESI had they been subject to the more stringent large firm employer mandate. The coverage shift estimate for SF-3 is noticeably higher, but is also less precise than the first three, resulting in a one standard deviation range of 42 to 82 percent. The first three estimates fall within this range, and are far more precise. The last three estimates in Table 1.4 (SF-4, SF-5, and SF-6) indicate smaller estimates of small firm ESI to subsidized insurance coverage shifts. The treatment effect on ESI was relatively similar to the baseline and to the first three alternative firm sizes, but the take up of subsidized coverage was much higher, resulting in a lower coverage shift estimate. This result is congruent with a larger pool of uninsured workers in small firms relative to large firms and with the incentive for exempt firms to rely more heavily on the Connector to subsidize their employees' health insurance.

Table 1.7 displays regression coefficients for the parameter of interest β on $(MA * Post * Small\ Firm)$ derived from the estimation of equation 1.3 for the baseline definition of firm size and baseline Northeast control group as well as for the nine other control groups listed in Table 1.5. The estimates from the baseline specification, and the alternative control group of the 48 contiguous states are very similar for all coverage outcomes, indicating that small-firm employees had a smaller ESI treatment effect as well as larger subsidized coverage and overall insurance rate effects. Both estimations yielded coverage shift estimates of approximately 50 percent. Additionally, the block bootstrap-t procedure produced results indicating significance of all estimates at the 5-percent level for the 48 contiguous states control group. Removing from the control group states that implemented less substantial health reforms over the analysis period did not substantially change the 50-percent coverage shift estimate either, indicating that these health reforms did not have a substantial impact on coverage distributions for lower-income workers. Testing for heterogeneity in firm response to different insurance market regulations by only analyzing states with both guaranteed issue and community rating resulted in similar results to the baseline model and a coverage shift estimate of 42 percent.

Table 1.7: Triple-Difference Estimation – Control Group Robust

	N	ESI	Subsidized Coverage	Uninsured	Coverage Shift
North East and Contiguous 48					
North East (Baseline)	40,696	-0.059	0.116	-0.057	0.507
		(0.021)**	(0.010)***	(0.016)***	(0.154)***
Contiguous 48	185,112	-0.065	0.126	-0.061	0.515
		(0.006)***++	(0.004)***+++	(0.005)***++	(0.041)***++
Less Substantial Health Reforms					
North East Limited	35,393	-0.056	0.117	-0.061	0.479
		(0.021)**	(0.011)***	(0.016)***	(0.157)***
Contiguous 48 Limited	159,401	-0.064	0.126	-0.062	0.509
		(0.007)***	(0.005)***	(0.006)***	(0.048)***
Community Rating and Guaranteed Issue					
Community Rating/Guaranteed Issue	17,036	-0.049	0.116	-0.068	0.419
		(0.025)*	(0.015)***	(0.021)**	(0.190)**
Migration Spillovers					
New England	15,987	-0.124	0.136	-0.011	0.916
		(0.018)***	(0.011)***	(0.018)	(0.129)***
New England Limited	10,684	-0.119	0.149	-0.030	0.797
		(0.029)***	(0.007)***	(0.026)	(0.177)***
North East with New England Removed	27,134	-0.051	0.115	-0.064	0.44
		(0.022)*	(0.011)***	(0.018)***	(0.170)***
Contiguous 48 with New England Removed	171,550	-0.063	0.126	-0.062	0.505
		(0.006)***	(0.004)***	(0.005)***	(0.042)***
Contiguous 48 with New England Removed Limited	151,142	-0.063	0.126	-0.063	0.503
		(0.007)***	(0.005)***	(0.006)***	(0.048)***

Notes: The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 who are between 133 and 300 percent FPL working in the private sector and not receiving any SSI or SSDI benefits. Standard errors for coefficients are clustered at the state level. Standard errors for the coverage shift estimates were calculated using the delta method. Significance based on asymptotic standard error estimation is indicated by *'s, *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level. Significance based on 10,000 sample draws for a block bootstrap-t with asymptotic cluster robust variance estimator refinement indicated by +'s, +++ indicates significance at the 1 percent level, ++ indicates significance at the 5 percent level, and + indicates significance at the 10 percent level.

The robustness test for the occurrence of migration spillovers generated estimates in line with the migration theory. The estimated ESI treatment effect is much more negative compared to the baseline, potentially due to small-firm workers migrating into Massachusetts to access subsidies, which closes the post-period treatment effect gap between small firms in Massachusetts and in the neighboring control states, while leaving the difference between large firms in Massachusetts and the control states unaffected. The estimated subsidized coverage treatment effect is slightly more positive than the baseline, potentially due to an increase in the take up of subsidized coverage among migrating small-firm workers and a decrease in lower-income workers who may have been on the Medicaid rolls in neighboring states. The overall insurance rate estimate is more positive and closer to zero than the baseline estimate, possibly due to the reduction of uninsurance rates in neighboring states due to migration. All of these estimates are congruent with a theory of migration, yielding an overestimate of coverage shifts. Removing New England from the Northeast and contiguous 48 states control groups yielded treatment effect estimates similar to the baseline model, resulting in a significant coverage shift estimate of 50 percent.

Table 1.8 displays regression coefficients for the parameter of interest β on $(MA * Post * Small\ Firm)_i$ derived from the estimation of equation 1.3 for the baseline definition of firm size (1-24 vs. 25+) and the baseline Northeast control group by FPL. The estimated small firm ESI to subsidized insurance coverage shift is much higher and more significant for lower-income workers. Lower-income workers have access to higher subsidies, so they have a greater incentive to switch from ESI to subsidized health insurance. The results for individuals above 300 percent FPL, and thus not eligible for subsidies, reveal that higher-income small-firm workers are more likely than large-firm workers to newly take up ESI coverage after the MHCI reform. These results are congruent with the heterogeneous distribution of ESI offer rates between small and large firms (99 percent of large firms and 54 percent of small firms offer ESI), as discussed in Section 1.6.

Table 1.8: Triple-Difference Estimation – FPL Heterogeneity

	N	ESI	Subsidized Coverage	Uninsured	Coverage Shift
Baseline	40,696	-0.059	0.116	-0.057	0.507
		(0.021)**	(0.010)***	(0.016)***	(0.154)***
FPL Heterogeneity					
$133 \leq FPL \leq 200$	14,220	-0.134	0.195	-0.061	0.688
		(0.023)***	(0.022)***	(0.028)*	(0.125)***
$200 < FPL \leq 300$	26,476	-0.023	0.072	-0.050	0.312
		(0.019)	(0.007)***	(0.013)***	(0.234)
$FPL > 300$	125,267	0.045	0.013	-0.058	N/A
		(0.006)***	(0.003)***	(0.009)***	

Notes: The pre-period is 2000-2006 and the post-period is 2008-2011. The sample is restricted to workers age 18 to 64 working in the private sector and not receiving any SSI or SSDI benefits. The control group used here is the North East. Standard errors for coefficients are clustered at the state level. Standard errors for the coverage shift estimates were calculated using the delta method. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

Table 1.9 displays regression coefficients for the parameters of interest derived from the estimation of equation 1.4 for the baseline definition of firm size (1-24 vs. 25+) and the baseline Northeast control group separated into finer pre- and post-periods. The “early pre-period” is 2000-2003, the “late pre-period” is 2004-2006, the “during period” is 2007, the “early post-period” is 2008-2009, and the “late post-period” is 2010-2011. The omitted period is the “late pre-period”; thus all estimates are relative to this pre-period. There is no statistically significant difference between the “early pre-period” and the “late pre-period.” There were positive and significant increases in both ESI for small firms in the “during period” relative to large firms, followed by no difference in the treatment effect between small and large firms in the “early post-period”; after this period there were large and significant reductions in ESI for small-firm workers in the “late post-period” relative to large firms. Take up of subsidized coverage throughout the during and post-periods was differentially higher for small-firm workers, and overall insurance rates increased for small-firm workers relative to large firm workers in all post-periods. These results are congruent with an adjustment period in which small-firm employers and employees adjust to the incentives to reduce labor costs and increase earnings, respectively.

Table 1.9: Triple-Difference Estimation - Heterogeneity in pre-period and post-period Trends

	ESI	Subsidized Coverage	Uninsured	Coverage Shift
*MA*Early Pre*Small Firm*	0.019	-0.011	-0.008	
	(0.033)	(0.009)	(0.033)	
*MA*During*Small Firm*	0.048	0.07	-0.118	
	(0.021)*	(0.010)***	(0.024)***	
*MA*Early Post*Small Firm*	-0.000	0.064	-0.064	0.006
	(0.024)	(0.006)***	(0.022)**	(0.378)
*MA*Late Post*Small Firm*	-0.092	0.154	-0.062	0.595
	(0.016)***	(0.007)***	(0.013)***	(0.091)***

Notes: The early pre-period is 2000-2003, the late pre-period is 2004-2006, the during period is 2007, the early post-period is 2008-2009, and the late post-period is 2010-2011. The sample is restricted to workers age 18 to 64 working in the private sector and not receiving any SSI or SSDI benefits. The control group used here is the North East. Standard errors for coefficients are clustered at the state level. Standard errors for the coverage shift estimates were calculated using the delta method. *** indicates significance at the 1 percent level, ** indicates significance at the 5 percent level, and * indicates significance at the 10 percent level.

To further check the robustness of these results, I used a synthetic control group approach. I solved equation 1.5 and assigned weights to each state. I assigned most states a weight of zero; I report the weights for each synthetic control group in Table 1.10. It is important to note here that of the 11 control states used in the triple-difference analysis, 10 show up with positive weights for at least one synthetic control group (New Jersey was not assigned a positive weight for any control group). These weights were applied to each state to construct synthetic control groups for each outcome in Massachusetts by firm size. Figures 1.10, 1.11, and 1.12 display the resulting synthetic control groups compared to Massachusetts. For each of the outcomes, the pre-trends for the synthetic control group match well to the pre-trends for Massachusetts.

Table 1.10: State Weights for Synthetic Control Groups

State	ESI-SF	ESI-LF	Subsidy-SF	Subsidy-LF	Uninsured-SF	Uninsured-LF
AZ	0.000	0.000	0.000	**0.177**	0.000	0.000
CA	0.000	**0.261**	0.000	0.000	0.000	0.000
CT	**0.407**	0.000	**0.508**	0.000	0.000	0.000
DC	**0.193**	**0.138**	0.000	**0.347**	**0.300**	0.000
DE	0.000	0.000	0.000	0.000	**0.206**	0.000
IA	0.000	0.000	0.000	0.000	**0.050**	0.000
MD	0.000	0.000	0.000	0.000	0.000	**0.502**
ME	0.000	0.000	**0.058**	**0.137**	0.000	0.000
MI	0.000	0.000	0.000	0.000	**0.052**	0.000
MT	0.000	0.000	0.000	0.000	0.000	**0.137**
NH	**0.074**	0.000	0.000	**0.178**	0.000	0.000
NY	0.000	0.000	0.000	**0.029**	0.000	0.000
OH	**0.259**	0.000	0.000	0.000	**0.231**	0.000
OR	**0.067**	0.000	0.000	0.000	0.000	0.000
PA	0.000	0.000	**0.169**	0.000	0.000	0.000
RI	0.000	**0.334**	**0.132**	**0.131**	**0.160**	0.000
TN	0.000	0.000	0.000	0.000	0.000	**0.002**
VA	0.000	0.000	0.000	0.000	0.000	**0.295**
VT	0.000	**0.267**	**0.133**	0.000	**0.001**	**0.064**

Notes: States which contributed zero weight for all synthetic control groups have been omitted from this table.

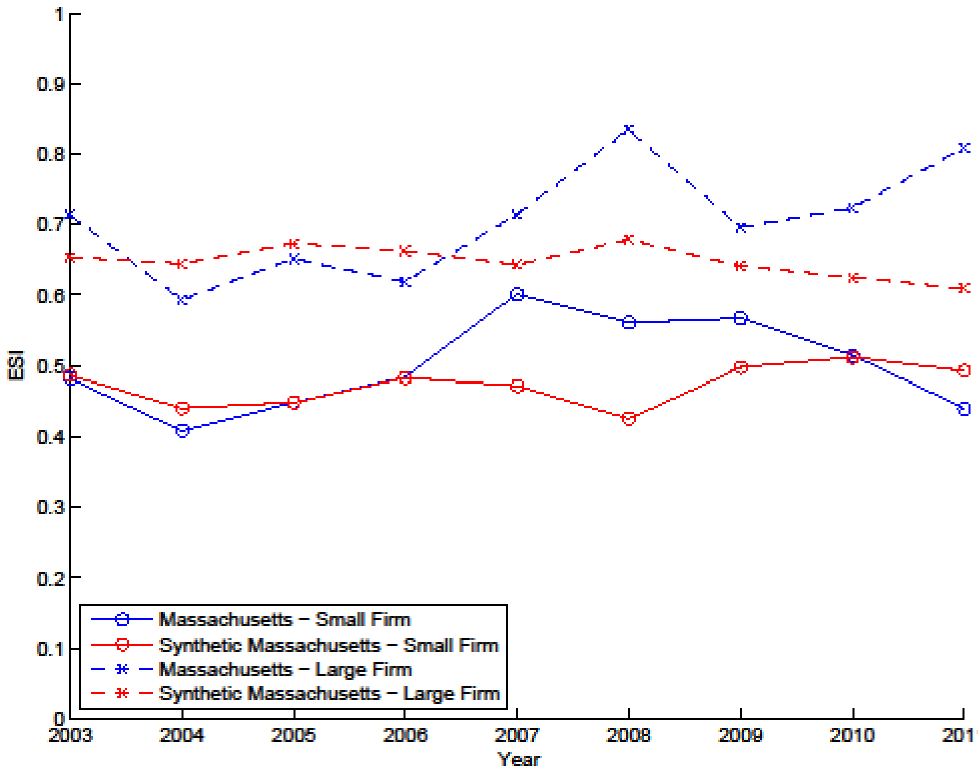


Figure 1.10: ESI: Massachusetts vs. Synthetic Massachusetts

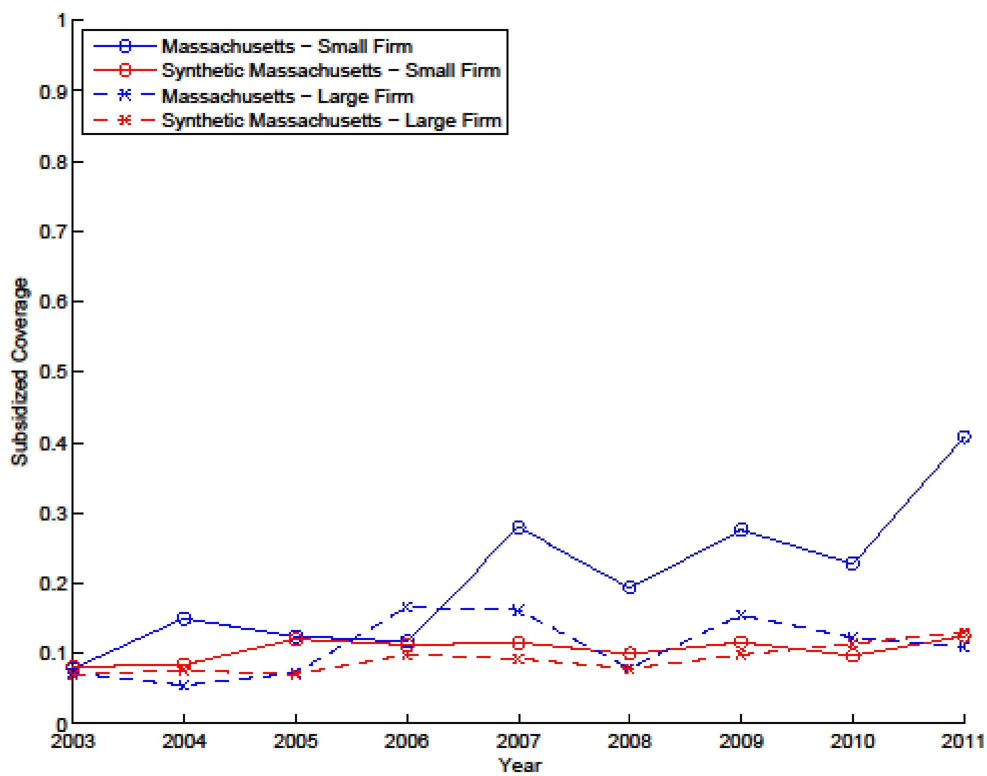


Figure 1.11: Subsidized Coverage: Massachusetts vs. Synthetic Massachusetts

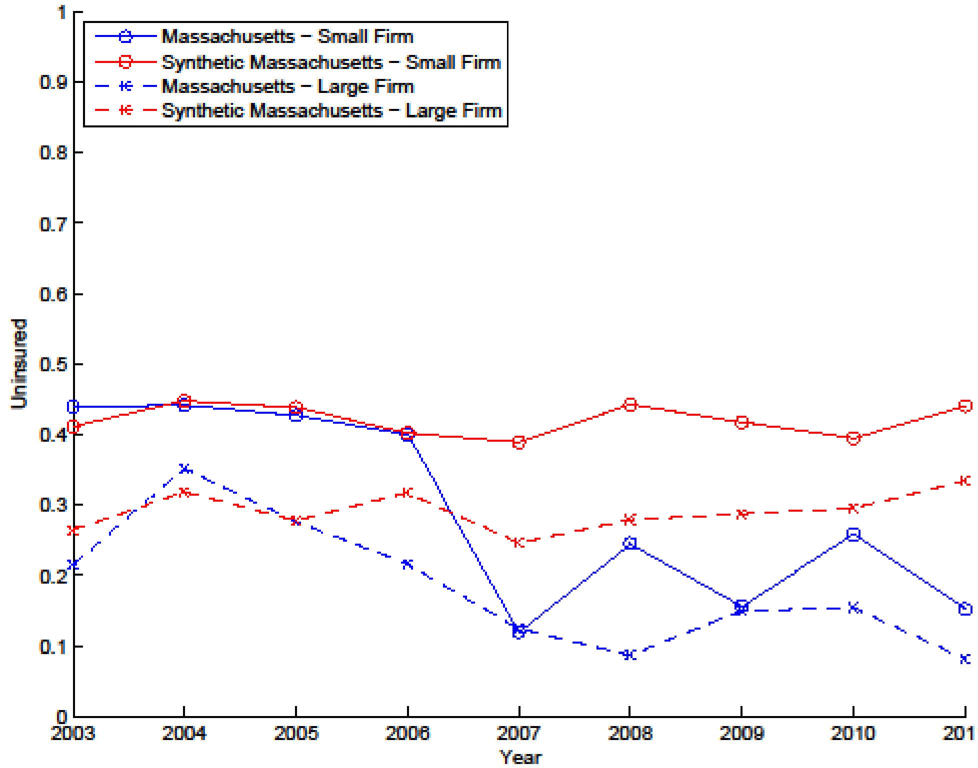


Figure 1.12: Uninsured: Massachusetts vs. Synthetic Massachusetts

To assess the significance of the treatment effect in Massachusetts for each of the insurance coverage outcomes (ESI, subsidized coverage, and uninsurance), I used the placebo method outlined in Abadie et al. (2010). Subsequently, I calculated the average treatment effect using years 2008-2011 for Massachusetts and all 48 placebo states and constructed an empirical and smoothed cumulative density function to see where Massachusetts' treatment effects fell relative to the placebo study. These results are presented in Figures 1.13, 1.14, and 1.15. The estimated average treatment effects in Massachusetts were all significant; the ESI treatment effect is significant at 10-percent level, the subsidized coverage treatment effect is significant at the 1-percent level, and the overall insurance rate treatment effect is significant at the 10-percent level. The treatment effects taken jointly are significant at the 1-percent level. The estimated average treatment effects on ESI, subsidized coverage, and uninsurance, respectively, are -9.42 percent, 15.11 percent, and -7.19 percent. Next, using equation 1.2 and the synthetic control group approach, I estimated small firm ESI to subsidized insurance coverage shifts to be 62.33. This estimate of the coverage shift parameter is higher than the estimate stemming from the triple-difference identification strategy. This is most likely due New England comprising most of the donor states. These states display evidence in line with a theory of migration spillovers which biases the coverage shift estimate upwards.

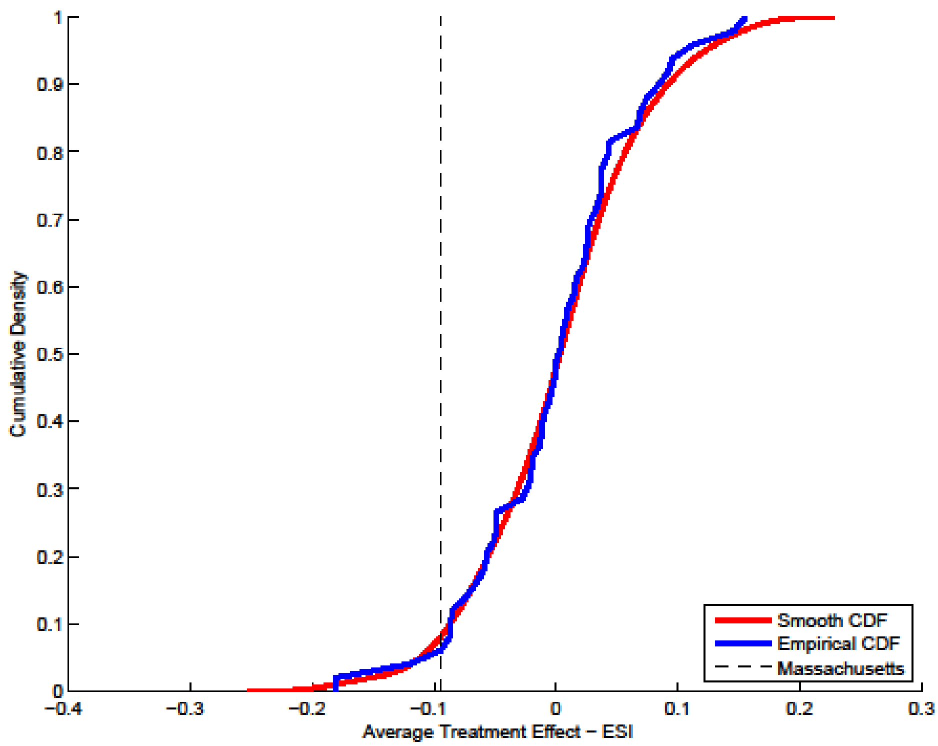


Figure 1.13: Significance of the Average Treatment Effect for ESI in Massachusetts

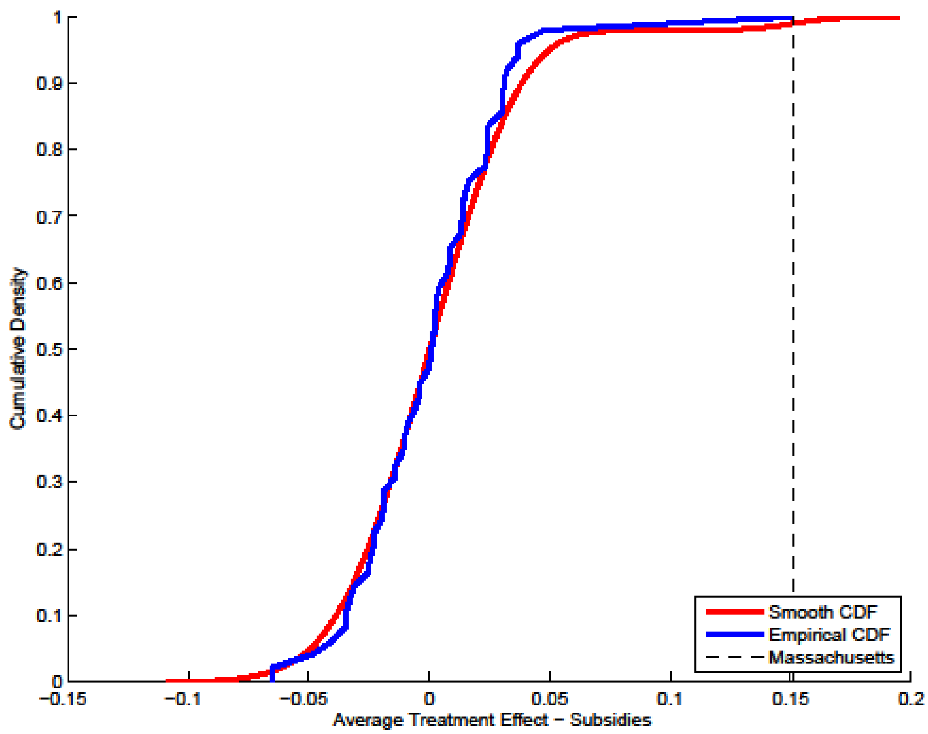


Figure 1.14: Significance of the Average Treatment Effect for Subsidized Coverage in Massachusetts

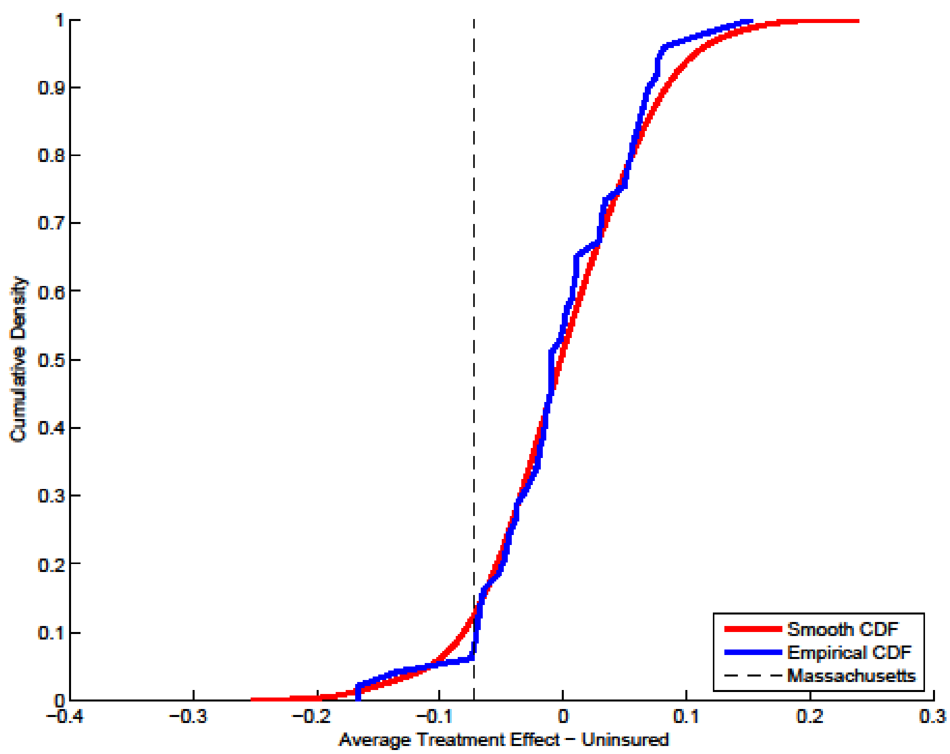


Figure 1.15: Significance of the Average Treatment Effect on the Uninsured in Massachusetts

Including the number of letters in a state's name as a variable in the estimation of equation 1.5 resulted in similar estimates of average treatment effects on ESI, subsidized coverage, and uninsurance. The specific estimates respectively are -10.46 percent, 15.13 percent, and -8.12 percent (*Coverage Shift* = 69.11 percent). It is important to note here that the inclusion of this variable did change the estimated weights for each insurance outcome and leaned heavily toward states with longer names. This occurred because Massachusetts has a relatively long name compared to other states. In fact, Washington DC and New Hampshire (which both have as many letters in their state names as Massachusetts) had positive estimated weights in more outcomes than in the original estimation. Table 1.11 displays the weights from this exercise. Despite obtaining similar results when including this variable, the dramatic change in the estimated weights should not be ignored, and it is noted that results from this method should be scrutinized heavily with respect to the variables chosen to be included in the estimation. This method still retains some merit as a data-driven robustness check that is congruent with my triple-difference estimates.

Table 1.11: State Weights for Synthetic Control Groups (Adding Number of Letters in State's Name)

State	ESI-SF	ESI-LF	Subsidy-SF	Subsidy-LF	Uninsured-SF	Uninsured-LF
AZ	0.000	**0.070**	0.000	0.000	0.000	0.000
CA	0.000	**0.141**	0.000	0.000	0.000	0.000
CT	**0.505**	0.000	**0.277**	0.000	**0.020**	0.000
DC	0.000	0.000	**0.033**	**0.390**	**0.131**	**0.150**
MI	0.000	0.000	0.000	0.000	**0.597**	0.000
NC	0.000	**0.587**	0.000	0.000	0.000	**0.337**
NH	**0.422**	**0.185**	0.000	**0.083**	**0.253**	**0.512**
NM	**0.073**	0.000	0.000	0.000	0.000	0.000
RI	0.000	0.000	**0.629**	**0.322**	0.000	0.000
VT	0.000	0.000	**0.060**	0.000	0.000	0.000
WV	0.000	0.000	0.000	**0.206**	0.000	0.000
WY	0.000	**0.018**	0.000	0.000	0.000	0.000

Notes: States which contributed zero weight for all synthetic control groups have been omitted from this table.

1.8 Conclusion

In this paper I investigate the extent to which more lenient mandates on small firms have differently impacted the movement of their workers onto government subsidized insurance rolls. I find that the relatively lenient treatment of small firms has generated enough incentives to noticeably change the pathways to health insurance coverage for small-firm workers. Evidence presented in this paper demonstrates a substantial and significant response on the part of small firms to the incentive to shift the burden of health insurance costs from the firm and the worker to taxpayers by sending their income-eligible employees to the Connector for subsidized coverage. Specifically, I find that almost all of newly subsidized coverage take-up is generated by small-firm employees and that one out of every two newly covered small-firm employees receiving subsidies would have obtained or maintained ESI had they been subject to the more stringent large-firm employer mandate. Additionally, the trade-off of not allowing these coverage shifts to occur by applying the large-firm mandate to all firms is estimated to be a 6 percent reduction in overall insurance rates for small-firm employees.

The results presented in this paper are robust to firm size definition, the elimination of states that implemented less substantial health reforms over the analysis period, limiting the control group to only states with guaranteed issue and community rating, migration spillover effects, and the creation of a synthetic Massachusetts. Additionally, when bootstrapping methods were appropriate, significance of the results was maintained. Testing for heterogeneity in the treatment effect of the MHCI by FPL, I find that lower-income working individuals are more likely to enroll in subsidized coverage. I also find no evidence of dissimilar impacts on coverage distributions between small- and large-firm employees immediately following MHCI implementation (2008-2009); I do find substantial differences since 2010, however, which indicate an adjustment period immediately following implementation.

These findings are congruent with an interpretation that small firms respond to the incentives embedded in the MHCI by sending relatively more of their income-eligible employees to the Connector for subsidized health insurance coverage compared to large firms. This effect is strongest among lower-income groups who have access to higher subsidies, and it is non-existent for workers not eligible for subsidized coverage (workers above 300 percent of the FPL). There appears to be an adjustment period immediately following MHCI implementation in which there is no evidence that small firms were responding to a relatively more lenient application of the employer mandate, but since 2010 small-firm employees have been taking up subsidized coverage at much higher rates than demographically similar large-firm workers. In fact, current ESI levels for income-eligible small-firm workers has fallen to pre-MHCI levels after an initial increase in the take-up of ESI.

The question of whether firms and employees respond differently to the MHCI employer mandate has both economic and policy relevant implications. Economically, one would expect small firms to respond to their more lenient employer mandate by sending more income-eligible employees to the Connector for subsidized coverage, resulting in fewer small-firm employees taking up ESI as compared to large-firm employees. This behavioral response on the part of small firms is due to the ease with which small firms can reduce the costs of hiring income-eligible workers by transferring health insurance costs to taxpayers. This paper provides evidence that small firms have in fact responded to the differential incentives embedded in the MHCI. The main policy conclusion that can be drawn from this paper is that in applying more lenient employer mandates to small firms, the MHCI increased overall health insurance coverage rates for small-firm employees by six percent. However, this increase in coverage rates comes at a cost. Specifically, the cost of increased health insurance coverage rates for small-firm employees is that half of the subsidized coverage pool would have otherwise obtained or maintained employer plans had small firms been subject to the more stringent large-firm employer mandate. More broadly, these results provide evidence that not only are employer mandates effective at maintaining ESI distributions, but also that the stringency of employer mandates has an impact on pathways to coverage for lower-income workers as well.

The ACA has a much more lenient definition of exempt small-firms[19], a much more stringent employer mandate on large firms[20], and much more generous income eligibility guidelines than the Massachusetts reform.[21] Thus, there exists a larger exempt population of small-firms and employees under the ACA due to both more generous income eligibility guidelines and a more lenient definition of exempt small-firms. Therefore, to the extent that firms and employees respond to the ACA's employer mandate similarly to firms and employees under the MHCI employer mandate, I would expect the more stringent requirements on large firms under the ACA to increase ESI offer and take up rates relative to the increases observed in Massachusetts. I would also expect a much larger share of the overall population in small firms to rely on subsidized exchange coverage due to the more lenient exemption criteria for small firms and more generous subsidy eligibility criteria under the ACA. Additionally, the federal government has postponed the employer mandate until 2015 which may have an impact on whether large firms decide to offer acceptable ESI or postpone offering until 2015.

---

[19] A small exempt firm under the ACA is one with less than 50 FTEs, while in Massachusetts and exempt small firm is one with less than 11 FTEs.
[20] Under the ACA a $2,000 per FTE fine is imposed if the employer does not offer acceptable coverage, while a $3,000 fine per employee is imposed if the employer offers coverage but employees are still able to access subsidies in the exchange. Massachusetts fines employers $295 per FTE for failing to comply with the "fair and reasonable" contribution mandate.
[21] Under the ACA individuals below 400 percent of the FPL are eligible for subsidies, while Massachusetts limits eligibility to those below 300 percent of the FPL.

As the ACA continues to roll-out and complete the implementation process in 2015, it will be crucial to track how employers and employees are responding to the incentives to offer and take up ESI relative to accessing subsidized coverage through the state run health insurance exchanges.

REFERENCES

Abadie, A., A. Diamond, and J. Hainmueller (2010). Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program. *Journal of the American Statistical Association*, 105(490):493-505.

Bertrand, M., E. Duflo, and S. Mullainathan (2004). How Much Should We Trust Differences-In-Differences Estimates? *The Quarterly Journal of Economics*, 119(1):249-275.

Blue Cross Blue Shield of Massachusetts, (2012). Health Reform in Massachusetts: Expanding Access to Health Insurance Coverage. Accessed at: https://www.mahealthconnector.org/portal/binary/com.epicentric.contentmanagement.servlet.ContentDeliveryServlet/Health%2520Care%2520Reform/Overview/HealthReformAssessingtheResults.pdf

Brown, C. (1980). Equalizing Differences in the Labor Market. *The Quarterly Journal of Economics*, 94(1):113-134.

Cameron, A., J. Gelbach, and D. Miller (2008). Bootstrap-Based Improvements for Inference with Clustered Errors. *The Review of Economics and Statistics*, 90(3):414-427.

Commonwealth Health Insurance Connector Authority, (2012). Health Reform Facts and Figures. Accessed at: https://www.mahealthconnector.org/portal/binary/com.epicentric.contentmanagement.servlet.ContentDeliveryServlet/Health%2520Care%2520Reform/Facts%2520and%2520Figures/Facts%2520and%2520Figures.pdf

Courtemanche, C. J. and D. Zapata (2014). Does Universal Coverage Improve Health? The Massachusetts Experience. *Journal of Policy Analysis and Management*, 33(1):36-69.

Gruber, J. (2008). Incremental Universalism for the United States: The States First Move? *Journal of Economic Perspectives*, 22(4):51-68.

Gruber, J. (2010). Health Care Reform is a "Three-Legged Stool": The Costs of Partially Repealing the Affordable Care Act. *Center for American Progress*. Accessed at: http://www.americanprogress.org/wp-content/uploads/issues/2010/08/pdf/repealing_reform.pdf

Kolstad, J. T. and A. E. Kowalski (2012a). The Impact of an Individual Health Insurance Mandate on Hospital and Preventive Care: Evidence from Massachusetts. *Journal of Public Economics*, 96(11-12):909-929.

Kolstad, J. T. and A. E. Kowalski (2012b). Mandate-Based Health Reform and the Labor Market: Evidence from the Massachusetts Reform. *NBER Working Paper 17933*.

Long, S. (2010). A Comment On "The Massachusetts Health Plan: Much Pain Little Gain." *Urban Institute Health Policy Center Brief*.

Long, S. and K. Stockley (2011). The Impacts of State Health Reform Initiatives on Adults in New York and Massachusetts. *Health Services Research*, 46(1-2):365-428.

Long, S., K. Stockley, and H. Dahlen (2012). Health Reform in Massachusetts as of Fall 2010: Getting Ready for the Affordable Care Act and Addressing Affordability. *Urban Institute Research Report*.

Long, S., K. Stockley, and A. Yemane (2009). Another Look at the Impacts of Health Reform in Massachusetts: Evidence Using New Data and a Stronger Model. *American Economic Review Papers and Proceedings*, 99(2):508-511.

Massachusetts Division of Health Care, Finance, and Policy, (2011). Health Care in Massachusetts: Key Indicators. Accessed at: http://www.mass.gov/chia/docs/r/pubs/11/2011-key-indicators-february.pdf

Massachusetts Division of Health Care, Finance, and Policy, (2013). Fair Share Contribution and Employer Health Insurance Responsibility Disclosure: Filing Year 2011 Results and Analyses. Accessed at: http://www.mass.gov/chia/docs/r/pubs/13/fsc-and-ehird-report-2011.pdf

Raymond, A. (2009). Massachusetts Health Reform: The Myth of Uncontrolled Costs. Massachusetts Taxpayer Foundation. Accessed at: http://www.masstaxpayers.org/sites/masstaxpayers.org/files/Health%20care-NT.pdf

Summers, L. (1989). Some Simple Economics of Mandated Benefits. *American Economic Review*, 79(2):177-183.

CHAPTER 2

AN OPTION DEMAND MODEL OF COMPETITION AND MARKET POWER IN PHYSICIAN PRACTICE GROUPS

2.1 Introduction

The assessment of market power for health care services is of considerable interest for antitrust purposes. Health care has been the most active area for antitrust enforcement over the past two decades, with over 1400 mergers and acquisitions successfully consummated between 1994 and 2009 (Kaiser Family Foundation, 2005; Irving Levin Associates, 2007, 2008, 2009, 2010). During much of this period, the antitrust agencies were largely unsuccessful in their attempted challenges to a number of these mergers, due largely to the acceptance by the courts of ad hoc market definition techniques that defined overly expansive markets and consequently a particularly permissive merger environment for hospitals (Gaynor et al., 2012). As a result a number of new approaches to inferring market power in health care markets have emerged in recent years.

A key insight of these models is the recognition of the unique role of intermediation by payers on behalf of patients. In health care markets, price negotiation between managed care organizations and providers in exchange for the inclusion of providers in a network is especially common. This process, termed selective contracting by Dranove et al. (1993) has become the basis for empirical economic models introduced by Town and Vistnes (2001) and Capps et al. (2003) that capture the bargaining leverage possessed by providers when negotiating with insurers. Recent application of these models have shown that hospital markets are largely local, and courts have been receptive to the conceptual framework inherent in these models, as applied to the bargaining context specific to the health care industry. In addition, the most recent revision of the authoritative Federal Trade Commission and Department of Justice merger guidelines (Federal Trade Commission and Department of Justice, 2010) has explicitly acknowledged the validity of alternative approaches to market analysis, including concepts that are closely related to the bargaining framework embodied in these models (Capps, 2012).

However, despite a considerable literature that has emerged analyzing market power in the hospital industry, little is known about the extent of market power for physician services. Physician services currently account for nearly one-fifth of health care expenditures in the United States (Martin et al., 2012) and recent evidence in a limited number of markets is suggestive of the ability of physician practices to bargain effectively with insurers (Ginsburg, 2010). Consequently, there exists a substantial need to develop reliable and economically sound methods for analyzing the effects of physician practice mergers. Anecdotal observation suggests that patients prefer to obtain physician services relatively close to where they work or live, suggesting the potential for relatively few physician groups within a small geographic area to exert market power in the event of a merger (American Bar Association, 2003). This may particularly be the case for primary care physicians, who are generally consulted more frequently than specialists, and typically generate referral patterns in a more localized area than do specialists. However, obtaining actual evidence on the extent of market power for physicians is particularly difficult, since in contrast to hospitals, data on patient origin, treatment location, and pricing of services that can be used to empirically examine market power is unavailable.

Evidence on the existence (or absence) of physician market power is especially important given provisions in the 2010 Affordable Care Act (ACA) that encourage the formation of Accountable Care Organizations (ACOs). While it is hoped that these ACOs will coordinate care across networks of providers and realize cost-reducing efficiencies, the coordination of providers through these organizations may potentially contribute to an increase in bargaining power among ACO participants, thereby resulting in higher health care prices in the private market. While the antitrust agencies have instituted "safe-harbor" guidelines for ACO formation that are intended to guard against anti-competitive practice arrangements, these guidelines are voluntary, and make use of patient-flow methods which have been shown to understate the degree of market power for health care providers (Elzinga and Swisher, Forthcoming; Gaynor et al., 2012).

This study makes use of Medicare Part B claims data for a 20% sample of Medicare beneficiaries enrolled in traditional Medicare (Fee-for-Service) for 2009 and physician pricing data from a database of private insurers to assess market power for physician practices. Using insights from Fournier and Gai (2007) and Farrell et al. (2011), the option demand model of Capps et al. (2003) is further developed and applied to three specialty physician markets (cardiology, oncology, and orthopedics) in a major metropolitan area. Results indicate the existence of market power for all specialty physician practices, and further the degree of market power varies across specialties within the market. The methods used here can be applied more generally to infer the degree of market power in physician and other health care provider markets.

The chapter proceeds as follows: Section 2.2 reviews the literature on market power for health care providers. Section 2.3 describes the adapted option demand model. Section 2.4 describes the data sets used. Section 2.5 presents the results. Section 2.6 concludes.

2.2 Market Power for Health Care Providers

A sizable literature exists on inferring market power for hospitals. Approaches to identifying market power in the academic literature have varied considerably (Gaynor and Vogt, 2000). The most common methods analyze firm concentration in specific geographic areas using either relatively large geopolitical units defined for other purposes such as counties or census divisions such as Metropolitan Statistical Areas (MSAs) or Health Services Areas (HSA) (Romeo et al., 1984; Lynk, 1995a; Dranove et al., 1992) or by constructing an area around a particular provider and encompassing all providers located in that area (Robinson and Luft, 1985; Gruber, 1994). Using the set of providers located in the geographic areas, concentration indices are typically constructed using providers in the market. The underlying assumption of this method is that within these defined boundaries, each provider could constrain the pricing decision of other providers in that market such that a price increase would not be profitable.

Recent literature has focused on identifying provider market power in health care markets using structural approaches. In these studies, patient choice and firm behavior are explicitly modeled and estimated using econometric techniques. Two of the most prominent of these models, developed by Gaynor and Vogt (2003) and Capps et al. (2003) estimate the extent of market power in the hospital industry using micro-data collected from hospital discharge records that enable direct estimation of patient preferences for hospital care. The model developed by Gaynor and Vogt (2003) is an adaptation of the methods set forth in Berry et al. (2004) which constructed a model of differentiated product oligopoly with Bertrand conduct. This model explicitly treats price as a component of consumer preferences under the implicit assumption hospital price in a consumer's utility function accurately captures a reduced form choice function incorporating the objectives of consumers and insurers. Capps et al. (2003) make the alternative assumption that prices do not enter directly into a consumer's choice framework. In this model, the decision of a consumer to join an insurance plan is determined by both the price of an insurance plan, as well as the network of providers included in each plan.

This framework allows providers that are more desirable to consumers to bargain more effectively with insurance companies, and thus command a higher price. Grennan (forthcoming), has derived the conditions under which these models coincide, however, they are similar in their empirical conclusions regarding the extent of market power for hospitals in that they both predict that the consolidation of a very small set of providers would significantly increase the price of health care services (Gaynor and Town, 2011).

The option demand model has been applied empirically and tested against actual merger outcomes. For example, Dranove and Sfekas (2009) applied the model to proposed consolidations in New York State and found that merging the only two hospitals in Elmira, NY could result in a price increase of 8%. Two related papers also show that these methods can provide reliable predictions of actual mergers (Fournier and Gai, 2007; Akosa et al., 2009). Fournier and Gai (2007) empirically tested the Capps et al. (2003) model against data from actual hospital mergers in both Florida and New York, and found that the Capps et al. (2003) model estimates price increases reliably, and conservatively. Akosa et al. (2009) tested a version of the structural Bertrand Pricing model and found that it produced accurate estimates of merger induced price increases. Gaynor et al. (2012) then compared the Capps et al. (2003) and the Bertrand Pricing models to each other and found that merger simulations from both models produced similar results.

However, despite the central role of physicians in providing medical services and coordinating care, the question of the extent of market power in physician markets is largely an unexplored topic. With the exception of a relatively recent study by Schneider et al. (2008) that provides evidence on the relationship between physician group practice concentration and price in

California counties, there is no good systematic information on the extent of market power in local physician markets (Gaynor and Town, 2011). The difficulty in analyzing physician markets is mainly due to the limited availability of data containing patient location, provider location and pricing information for physician services. Anecdotal observation suggests the potential for physicians to leverage market power in geographically small markets because patients typically prefer to obtain physician services close to where they work or live (American Bar Association, 2003). This is particularly true for primary care physicians, who are generally consulted more frequently than specialists and typically generate referral patterns in a more localized area than do specialists. However, obtaining actual evidence of market power for physician practices is notoriously difficult. This is because, in contrast to hospital mergers, data on patient origin, treatment location, and pricing of services that can be used to examine market power is generally unavailable for physician services. Consequently, very little empirical evidence exists pertaining to market power in physician markets.

Within the market for physician services, antitrust enforcement has addressed anticompetitive conduct along multiple dimensions, much of which requires (either implicitly or explicitly) the delineation of geographic markets. For example, Independent Practice Associations (IPOs) and Physician Hospital Organizations (PHOs) have represented attempts by physicians to increase their bargaining leverage with insurers, while attempts by physicians to gain exemption from antitrust laws and allow for collective bargaining have resulted in statements by the Federal Trade Commission (FTC) and the Department of Justice (DOJ) alleging that such exemptions would harm consumers by increasing costs without producing improvements in the quality of care (Federal Trade Commission and Department of Justice, 2004). Implicit in such policies is the assumption of the presence of market power in physician markets; that is physicians have the ability to extract excess profits by engaging in collusive conduct intended to limit competition. Furthermore, in response to the provisions encouraging the formation of Accountable Care Organizations (ACOs) in the Patient Protection and Affordable Care Act of 2010 (PPACA) the FTC and the DOJ have issued voluntary guidelines outlining criteria for evaluating whether an ACO may raise significant competitive concerns and thus warrant antitrust scrutiny.

In addition, the assessment of market power has become increasingly salient in recent antitrust cases involving physician services. For example, in Little Rock Cardiology Clinic v. Baptist Health, 591 F.3d 591 (8th Cir. 2009), the court rejected claims by the plaintiffs (Little Rock Cardiology Clinic) that the defendants (Baptist Health) were engaged in an attempt to restrain trade and monopolize a market on the grounds that practices outside of Little Rock were sufficiently close substitutes for practices in Little Rock such that the defendant could not profitably increase the price of services. Market power for physician practices has also been a fundamental issue of contention in physician cases such as Morgenstern v. Wilson, 29 F.3d 1291 (8th Cir. 1994), where an appeals court reversed the ruling of a lower court's decision that a group of cardiac surgeons in Lincoln, Nebraska had monopolized the market for cardiac surgery. A key factor in the court's decision to reverse the lower court's ruling was that the "plaintiff's geographic market was, as a matter of law, too narrow", thereby implying the existence of a limited scope of market power for these surgeons within the local market.

Ginsburg (2010) notes that providers in California have implemented strategies that have strengthened their market power, thus increasing their bargaining power with private health plans. This study further stresses that proposals to promote the formation of ACOs could lead to harmful increases in rates for physician services in the private market. The wide variation in private insurer physician reimbursement across and within local markets is indicative that some physician group practices have significant market power, thereby enabling them to extract prices above the competitive level (Berenson et al., 2010). Both Ginsburg (2010) and

Berenson et al. (2010) underscore the need to develop reliable and implementable methods to assess physician market power.

2.3 Model Adaptation and Methods

A key determinant of provider pricing in the health care industry is the bargaining process between providers and insurers over provider network composition (Capps, 2012). The insurers negotiate with providers over fee schedules, where insurers possesses bargaining power over providers through the threat of excluding them from their network (thus limiting the set of consumers that could potentially use the provider's services), and a provider's bargaining power stems from the threat of not allowing the insurance company to include them in their network (thus making the network less desirable to consumers). Once the bargaining process has concluded, the insurers have built a network which they can then offer to consumers. Consumers then choose an insurer based on the price (premiums, deductibles, co-payment, etc.) and access to providers that the network grants. More specifically, a provider weighs the negotiated price against the cost of serving an insurers patient population, and an insurer weighs the willingness to pay of their consumers to have access to a particular provider against the costs of including the provider in their network (Capps, 2012). And consumers' willingness to pay for access to a provider is directly tied to the number of substitute hospitals in a geographic location.

The Capps et al. (2003) option demand model is particularly well suited for an application to physician group practice market power as it incorporates these institutional features into its modeling framework. The two step process in which insurers bargain with physicians and then insurers market their network to consumers is a reasonable representation of the process by which physician practices bargain with insurers (Berenson et al., 2010). First, insurance companies bargain with physician group practices, where the insurer weighs the willingness to pay of their consumers for access to the physician group practice against to costs of including the practice in their network. The difference between the willingness to pay of an insurer's consumers and the cost of inclusion is the surplus from bargaining. Upon successful negotiations (the insurer contracts with the physician practice) the surplus from bargaining is shared between the practice and the insurer, depending on their relative bargaining power. The share that the physician practice group receives is translated into the price they are paid for their services to members of an insurer's network. This price, in theory, is directly tied to the consumers' willingness to pay (the mechanism through which a physician practice derives its bargaining power). Thus, one could think of a physician practice group having a reservation price for their services (the minimum they are willing to accept to provide a service), and the more desirable they are, the higher the price they can extract from the insurer. The model described below accounts for this bargaining process as well as the ability of physician practices to translate their desirability (consumers' willingness to pay) into higher reimbursements for services rendered.

2.3.1 Option Demand Model and Relevant Assumptions

In the Capps et al. (2003) Option Demand Model the ex-post decisions (the decision to seek medical services subsequent to the realization of illness) of consumers to select specific physicians is independent of price, while the ex-ante decision of a consumer to select a specific insurer is jointly determined by the network of providers offered by the insurer and the price charged by the insurer. This framework allows more desirable physician practice groups to have increased bargaining power with insurers due to the higher willingness to pay (WTP) of consumers to include these preferred physicians in their network.

The goal of this model is to calculate each consumer's ex-ante willingness to pay (WTP) to include a particular physician in an insurance company's network. The ex-ante WTP is a consumer's WTP to have access to a particular physician practice prior to any realization of illness resulting in a physician visit. The sum of the individual ex-ante WTP over all consumers is the ex-ante value that a physician group practice brings to the network. The interim WTP, which is the consumers WTP conditional on the realization of illness, is first estimated as an intermediate step in the calculation of ex-ante WTP. The first step in implementing this model is to estimate the parameters of consumers' ex-post expected utility function. The ex-post expected utility that patient *i* receives from selecting physician practice *j* is (equation 2.1):

$$U_{ij} = \alpha R_j + H_j' \Gamma X_i + \tau_1 T_{ij} + \tau_2 T_{ij} X_i + \tau_3 T_{ij} R_j - \gamma(X_i) P_j(Z_i) + \varepsilon_{ij}$$

$$= U\big(H_j, X_i, \lambda_i\big) - \gamma(X_i) P_j(Z_i) + \varepsilon_{ij}$$

Where $H_j = [R_j; S_j]$ is a column vector of location specific physician practice *j*'s characteristics. R_j includes number of practitioners, share of practitioners that are primary care physicians, number of services performed, and an indicator for the presence of physician assistants (PAs) or nurse practitioners (NPs). S_j includes condition and procedure specific offerings such as whether physician *j* performs vaccinations or serves patients diagnosed with congestive heart failure. The vector $X_i = [Y_i; Z_i]$ is patient *i*'s type and includes demographic characteristics (Y_i = age, sex and race) and clinical attributes (Z_i = diagnosis history, past diagnosis history as well as current procedure and diagnosis). $P_j(Z_i)$ is physician *j*'s out of pocket payment from patient *i* with clinical attributes Z_i. λ_i is the zip code of patient *i*'s home, and T_{ij} = $T_j(\lambda_i)$ is the distance (in miles) from patient *i*'s home to practice *j*'s location. Distance is one of the most important predictors of a patient's choice of physician (Cohen and Lee, 1985; Burns and Wholey, 1992; Capps et al., 2001; Varkevisser and van der Geest, 2006; Mayer, 1983). The function $\gamma(\cdot)$ coverts money into utility terms. And ε_{ij} is the idiosyncratic shock to patient *i*'s utility evaluation of practice j, and is assumed to be distributed i.i.d extreme value.[22]

It is important to note that claims data does not allow me to observe consumers choosing not to engage in the physician services market. This makes the specification of an outside option (insured individuals choosing not to use physician services) impossible. Thus, following the methods of Capps et al. (2003), I assume there is a captive market of patients who must choose to see a physician.

The utility parameters in equation 2.1 $(\alpha, \Gamma, \tau) = [\tau_1\ \tau_2\ \tau_3]$ represent the unconditional marginal values of physician practice attributes, patient specific values of practice location characteristics and travel costs respectively.

Patient *i* will select physician practice *j* if, for all physician practices $k \neq j$ (equation 2.2),

$$\alpha(R_j - R_k) + (H_j - H_k)'\Gamma X_i + \tau_1(T_{ij} - T_{ik}) + \tau_2(T_{ij} - T_{ik})X_i + \tau_3(T_{ij}R_j - T_{ik}R_k)$$
$$+ \gamma(Y_i, Z_i)(P_j - P_k) = U(H_j, X_i, \lambda_i) - U(H_k, X_i, \lambda_i) > \varepsilon_{ik} - \varepsilon_{ij}$$

Patients in the estimation sample will be selected to have health insurance for which there is no meaningful difference in the out-of-pocket price charged by different providers. Thus, the price difference between physician *j* performing procedure *x* and physician *k* performing procedure *x* for a patient in the sample is zero. Therefore, the term $\gamma(Y_i, Z_i)(P_j - P_k)$ vanishes. And, under the assumption that ε_{ij} is distributed i.i.d. extreme value, the probability

[22] As Capps et al. (2003) note, the utility specification in equation 2.1 allows for flexible substitution patterns across physician group practices due to the interaction of patient and provider characteristics. Therefore, this facilitates plausible own and cross price elasticities of demand and mitigates the problems associated with the independence of irrelevant alternatives (IIA) assumption in simple logit demand models.

that patient *i* chooses practice *j* takes on the following closed form of the logit demand formula (equation 2.3):

$$S_j(G, X_i, \lambda_i) = \frac{\exp\left[U\left(H_j, X_i, \lambda_i\right)\right]}{\sum_{g \in G} \exp[U\left(H_g, X_i, \lambda_i\right)]}$$

Where G is the set of all physician practice locations within a geographic area. In line with Capps et al. (2003), I assume that each insurer's network includes all physician practices. This assumption is necessary because I cannot observe the set of physician practices that consumers can access through their network. The utility parameters in equation 2.1 are estimated using maximum likelihood from the implied likelihood function of equation 2.3. The parameter $\gamma(\cdot)$ is left unidentified, this is resolved by Capps et al. (2003) by assuming $\gamma(\cdot) = \gamma$, a constant, implying that all WTP estimates will be identified up to an unknown scalar γ.

Subsequent to estimating the underlying parameters of the ex-post utility function, I can now calculate the interim expected utility for access to physician network G of patient *i* using the following equation (equation 2.4):

$$V^{IU}(G, Y_i, Z_i, \lambda_i) = E \max_{\mathrm{g} \in \mathrm{G}} [U\left(H_g, Y_i, Z_i, \lambda_i\right) + \varepsilon_{ig}] = \ln \sum_{g \in G} \exp[U\left(H_g, Y_i, Z_i, \lambda_i\right)]$$

Thus, physician practice *j*'s contribution to interim utility is simply the difference between interim utility with network G and interim utility with network $G \setminus j$.[23]

[23] $G \setminus j$ is the entire network G with physician practice *j* excluded.

$$\Delta \mathrm{V}_{\mathrm{j}}^{\mathrm{IU}}(G, Y_i, Z_i, \lambda_i) = V_j^{IU}(G, Y_i, Z_i, \lambda_i) - \mathrm{V}_{\mathrm{J}}^{\mathrm{IU}}(G \backslash j, Y_i, Z_i, \lambda_i)$$

$$= \ln \sum_{g \in G} \exp\left[U\left(H_g, Y_i, Z_i, \lambda_i\right)\right]$$

$$- \ln \sum_{k \in G \backslash j} \exp[U(H_k, Y_i, Z_i, \lambda_i)]$$

$$= \ln \frac{\sum_{g \in G} \exp\left[U\left(H_g, Y_i, Z_i, \lambda_i\right)\right]}{\sum_{k \in G \backslash j} \exp[U(H_k, Y_i, Z_i, \lambda_i)]} = \ln \left(\frac{\sum_{k \in G \backslash j} \exp[U(H_k, Y_i, Z_i, \lambda_i)]}{\sum_{g \in G} \exp\left[U\left(H_g, Y_i, Z_i, \lambda_i\right)\right]}\right)^{-1}$$

$$= \ln \left\{ \left[\sum_{k \in G \backslash j} \frac{\exp[U(H_k, Y_i, Z_i, \lambda_i)]}{\sum_{g \in G} \exp\left[U\left(H_g, Y_i, Z_i, \lambda_i\right)\right]} \right]^{-1} \right\}$$

$$= \ln \left(\sum_{k \in G \backslash j} s_k(H_k, Y_i, Z_i, \lambda_i) \right)^{-1} = \ln \left(1 - s_j\left(H_j, Y_i, Z_i, \lambda_i\right)\right)^{-1}$$

$$= \ln[\frac{1}{1 - s_j(H_j, Y_i, Z_i, \lambda_i)}]$$

$\Delta \mathrm{V}_{\mathrm{j}}^{\mathrm{IU}}(\cdot)$ can be converted to interim WTP by dividing by γ. Thus, the interim WTP to have access to physician $j \in G$ is (equation 2.5):

$$\Delta W_j^{IU}(G, Y_i, Z_i, \lambda_i) = \frac{\Delta V_j^{IU}(G, Y_i, Z_i, \lambda_i)}{\gamma}$$

Suppose $f(Y_i, Z_i, \lambda_i)$ is the joint density of demographics, clinical attributes, and locations of patients homes and $f(Z_i | Y_i, \lambda_i)$ is the conditional density of clinical attributes given demographics and location of patient *i*, then patient *i*'s ex-ante WTP to include physician practice *j* in network G is (equation 2.6):

$$\Delta W_{ij}^{EA}(G, Y_i, \lambda_i) = \int_Z \Delta W_j^{IU}(G, Y_i, Z_i, \lambda_i) f(Z_i|Y_i, \lambda_i) dZ_i$$

$$= \frac{1}{\gamma} \int_Z \Delta V_j^{IU}(G, Y_i, Z_i, \lambda_i) f(Z_i|Y_i, \lambda_i) dZ_i$$

And summing equation 2.6 over all patients yields the population's ex ante WTP to have access to physician practice $j \in G$ (WTP for *j*). Equation 2.7:

$$\Delta W_j^{EA}(G) = N \int_{Y,\lambda} \Delta W_j^{IU}(G, Y_i, Z_i, \lambda_i) f(Y_i|\lambda_i) dY_i d\lambda_i$$

$$= \frac{N}{\gamma} \int_{Y,Z,\lambda} \ln\left[\frac{1}{1 - s_j(G, Y_i, Z_i, \lambda_i)}\right] f(Y_i, Z_i, \lambda_i) dY_i dZ_i d\lambda_i$$

2.3.2 Bargaining Parameter Estimation

Conceptually, a physician practice group's price is a reflection of consumer's WTP. The more desirable the practice group, the more surplus the practice group can extract from the insurer. Therefore, higher WTP to include a physician practice in a network translates directly into higher prices. This conceptual framework can be represented by a Nash bargaining model in which insurers and physicians agree upon a price such that the product of the profits of physicians and insurers is maximized, subject to the bargaining power each player possesses. Formally, price is chosen according to the following game (equation 2.8):

$$\max_{p_j} \left[rvu_j(p_j - mc_j)\right]^{b_j} \left[\gamma\tau\Delta W_{ij}^{EA} - p_j rvu_j\right]^{b_m}$$

Taking the log of both sides and looking at the first order condition with respect to p_j (equation 2.9),

$$p_j = \frac{b_m}{b_m + b_j} mc_j + \frac{b_j}{b_m + b_j} \gamma\tau \frac{\Delta \mathrm{W_{ij}^{EA}}}{\mathrm{rvu_j}}$$

Thus, if MCO's have all of the bargaining power $\left(\frac{b_m}{b_m+b_j}=1\right)$ then $p_j = mc_j$ and if physicians have all of the bargaining power $\left(\frac{b_j}{b_m+b_j}=1\right)$ then $p_j = \gamma\tau\frac{\Delta\mathrm{W}_{\mathrm{ij}}^{\mathrm{EA}}}{\mathrm{rvu_j}}$ (they extract all of the surplus from bargaining). Let $\alpha = \frac{b_m}{b_m+b_j}mc_j$ and $\beta = \frac{b_j}{b_m+b_j}\gamma\tau$, then the equilibrium price can be represented by the following equation (equation 2.10):

$$p_j = \alpha + \beta\frac{\Delta W_j^{EA}(G)}{rvu_j}$$

Assuming that the price index is measured with mean zero normally distributed measurement error, the equilibrium price can be estimated via an OLS regression of the form (equation 2.11):

$$p_j = \alpha + \beta\frac{\Delta W_j^{EA}(G)}{rvu_j} + u_j$$

The key intuition here is that the sign and statistical significance of each of the parameter estimates of α and β is important in interpreting the results. A positive and statistically insignificant estimate, or an estimate of zero for α in conjunction with a positive and statistically significant estimate for β indicates that insurers have very little bargaining power relative to physicians, while the converse indicates that insurers possess most of the bargaining power relative to physicians. A positive and statistically significant estimate of both parameters indicates that both physicians and insurers have bargaining power. And, any negative and statistically significant estimate for β is evidence against the option demand model or the specification used to estimate the model.

2.3.3 Simulation of Physician Practice Mergers

This can be done by evaluating the increase in WTP associated with the merger of practice *j* and practice *k* as compared to the WTP of each practice separately. The method used here is identical to the method outlined in Capps et al. (2003). First the WTP to include practice *j* and *k* jointly is estimated by the following equation (equation 2.12):

$$\Delta W_{j+k}^{EA}(G) = \frac{N}{\gamma}\int_{Y,Z,\lambda} \ln\left[\frac{1}{1 - s_j(G,Y_i,Z_i,\lambda_i) - s_k(G,Y_i,Z_i,\lambda_i)}\right] f(Y_i,Z_i,\lambda_i)dY_i dZ_i d\lambda_i$$

The change in price is then estimated with the following formula (equation 2.13):

$$\Delta p_{j+k} = \frac{\hat{\beta}}{Q_{j+k}}\left[\Delta W_{j+k}^{EA}(G) - \left(\Delta W_j^{EA}(G) + \Delta W_k^{EA}(G)\right)\right]$$

Where $\hat{\beta}$ is the coefficient estimated from equation 2.11 and Q_{j+k} is the total number of services performed by practices *j* and *k* (in relative value units).

Conditional of finding a positive and significant slope parameter from estimating equation 2.11, the formula in equation 2.13 can be used to analyze the potential effect of a merger between two physician practice groups.

2.4 Data

A main reason for the lack of evidence regarding physician market power is the lack of sufficiently detailed data to allow for such analysis. Assessing market power for physician services requires the simultaneous identification of patient location, physician location, information on physician practice arrangements, and private prices (allowed amounts). The data sets used to overcome these limitations are described below.

2.4.1 Patient Level Data

Estimation of the parameters of the utility specification in equation 2.1 makes use of the Research Identifiable Files (RIF) of the Medicare Part B claims data for the year 2009 that includes final action claims data submitted by non-institutional Medicare providers for a 20% sample of Medicare beneficiaries. Examples of non-institutional providers include physicians, physician assistants, clinical social workers, nurse practitioners, independent clinical laboratories, ambulance providers, and free-standing ambulatory surgical centers. Information contained in this _le includes diagnosis and procedure codes (ICD-9 diagnosis, CMS Common Procedure Coding System (HCPCS) codes), dates of service, reimbursement amount to provider and non-institutional provider numbers (e.g., NPI). Particularly important to the analysis is the availability in these data of beneficiary demographic information including a 5-digit zip code, and provider location (including a 5-digit provider zip code) that allow for the inclusion of distance from patient zip code to provider zip code.

The analysis data set was constructed at the patient claim level, containing patient demographic information, clinical characteristics of the patient, and provider characteristics for the group practice location. Only the subsample of patients that visited s given specialists are included. A provider’s specialty is based on the information provided at the claim level. For example, if a provider submitted two claims, one as a family practitioner and another as a cardiologist, then only the claim submitted as a cardiologist was included in the sample to estimate WTP for cardiology practice groups.

2.4.2 Private Pricing Data

Private pricing data was obtained from the FAIR Health Database, which is the largest collection of private medical claims in the United States. The database contains over 14 billion billed medical and dental services for over 125 million insured plan participants. These data contain non-institutional provider numbers (NPI), physician location (zip code), diagnosis and procedure codes, and private reimbursements. The Medical Surgical claims data for 2009 was used to determine a private price index for three physician specialties (cardiology, oncology, and orthopedics). The price index uses the CMS Relative Value Units (RVUs) that are assigned to each procedure code. CMS assigns a practice expense RVU, a malpractice RVU and a physician work RVU. RVUs are designed to assign a standardized value to the services offered by physicians which CMS uses as basis for physician reimbursement. The private pricing data was limited to in-network claims to avoid anomalies inherent in out-of-network private insurance reimbursements.

The use of RVUs to construct price measures has been used by Dove (1994) to construct a single price scaling factor for a private insurer. The use of RVUs to generate a single price index for physician practices is only valid if RVUs accurately reflect the cost differences across procedures. The use of RVU’s as a tool to assess prices has been both praised as a mechanism for assigning a standardized unit of value to physician services (Dove, 1994) and criticized for not reflecting cost variation across specialties (Cooper and Kramer, 2008). However, given my focus on individual specialties separately this is unlikely to present a problem. Furthermore, Ginsburg (2010) reports that RVU conversion factors are the basis over which insurers and physicians set prices.

The private price index for each physician is computed by first taking the sum of the practice expense, physician work, and malpractice RVUs for each service performed by the physician and then summing this value over all services performed by the physician. The private reimbursement amounts over all services performed by the physician are then summed up for each physician. The price index is then calculated by dividing the total reimbursement for the physician by the sum of the RVU's to get a dollars per RVU measure of private prices. Formally (equation 2.14):

$$p_j = \frac{\sum_{k=1}^{K} Private\ Allowed\ Amount_k}{\sum_{k=1}^{K}(Work\ RVU_k + Expense\ RVU_k + Malpractice\ RVU_k)}$$

Where p_j is the case-mix adjusted price index for physician j, and k indexes the number of services offered by physician j.

2.4.3 Private Practice Price Index

In order to analyze patient choice over the physician group practice (and not the individual physician), I generate a single price index for the physician practice group. To construct this measure, I link the individual physician private price index to the Medicare claims by the provider NPI. A practice private price index was computed by aggregating the private price index over all physicians within the same employer identification number (EIN) and weighting by the RVUs for each physician.[24] [25]

2.4.4 Matching Medicare Data to Private Pricing Data

The FAIR Health data requires validation of provider NPIs. The reason that one major metropolitan area was chosen for this analysis was that the market chosen had one of the highest percentages of private claims reporting a positive reimbursement with a valid NPI[26] that matched to the Medicare data. This percent match criteria was weighed against the

---

[24] The use of EINs has been employed in previous studies of physician groups, and is used to identify group practices in Medicare demonstration projects (Pham et al., 2007; Centers for Medicare & Medicaid Services, 2011, 2010).
[25] In the instances where I could not compute a private price index for a physician within a group practice, I used the private price indices from the other physicians in the same group to generate the practice private price index. This approach requires the assumption that physician practices negotiate with insurance companies for reimbursement at the practice level.
[26] NPIs were validated using the checksum algorithm.

number of claims reported in a Core Based Statistical Area (CBSA), and the CBSA chosen, with a 62.43% match rate for approximately 4.1 million claims, was chosen over several other CBSAs which had a higher match rate, but significantly less claims. The CBSA chosen provided a reasonable number of claims per physician required to develop a reliable price index for the specialty practice groups.[27]

2.4.5 Caveats

The use of the Medicare population to estimate market power in the private non-Medicare market requires a fairly strong assumption. The determinants of physician choice for Fee-for-Service Medicare beneficiaries must be similar to the factors that determine physician choice in the private insurance market. This assumption may be violated if: 1) Medicare patients, who are mostly elderly, have different criteria by which they select physicians than younger patients who are insured through the private insurance market; 2) Determinants of physician selection is affected by Fee-for-Service Medicare patients generally having free choice of provider, thus not subject to financial steering that may be present in markets for privately insurance patients; 3) The absence of data on patients in the Medicare Advantage (MA) program creates a self-selection problem in that there may be significant differences between the FFS and the MA populations. Despite these strong assumptions, these data make the assessment of market power in physician markets feasible and more complete than has been previously implemented.

2.5 Results

This section describes the results from estimating the option demand model. The option demand model was estimated using claims from three physician specialties (cardiology,

[27] The FAIR Health data was first limited to the chosen CBSA and then matched by the validated NPI.

oncology, and orthopedics) in a single large CBSA. Summary statistics of all patients included in the sample are described in Table 2.1.

Table 2.1: Patient Variables (N = 373,050)

Variable	Mean	Standard Deviation
Female	0.573	0.495
Age	73.338	11.100
White	0.867	0.339
Inpatient/Outpatient	0.963	0.189
Long Term Care	0.336	0.472
Major Diagnosis	0.909	0.287
Minor Diagnosis	0.985	0.120

Notes: A history of a "Minor Diagnosis" is defined by any history of cataracts, glaucoma, COPD, osteoporosis, or arthritis. A history of a "Major Diagnosis" is defined by any history of Alzheimer's disease, dementia, atrial fibrillation, congestive heart failure, ischemic heart disease, acute myocardial infarction, cancer (endometrial, breast, colorectal, lung, or prostate), diabetes, hip fracture, or stroke. "Long Term Care" includes skilled nursing facility stays and home health visits.

Table 2.2 displays the list of variables included in the choice model by type and the estimates of the utility parameters are presented in Tables 2.3, 2.4, and 2.5. It is important to note here that the sign of the estimate for the coefficient on distance is negative and highly significant and most of the interactions terms are significant as well, indicating varying substitution patterns across patient types. The choice model was estimated at the claim per physician location level to allow patients to have preferences over multiple service locations within the same practice, while the WTP to include a practice was aggregated up to the practice level. Thus, the WTP measures included in Tables 2.6, 2.7, and 2.8 are reported at the practice level (and not just one specific location within a practice). The five types of variables in the choice model are provider characteristics common across all patients (R_j) and their interactions, distance from patient to provider (T_{ij}) and its interactions with provider characteristics ($T_{ij} \cdot R_j$), distance interacted with patient specific clinical and demographic variables ($T_{ij} \cdot X_i$), interaction of patient characteristics with hospital characteristics ($R_j' \cdot \Gamma_1 \cdot X_i$), and interactions of diagnosis and procedure codes of patients with diagnosis and procedure codes performed by the practice ($S_j' \cdot \Gamma_2 \cdot Z_i$).

Table 2.2: Predictor Variables Included in the Logit Demand Model, by Type

Variable Type	Variable	Interaction Variable
Provider Characteristics (R_j)	Number of services performed at practice location (# SRVC)	N/A
	Number of providers at practice location (# PROV)	N/A
	Share of primary care physicians at practice location (SHARE PC)	N/A
	Location employs NPs and/or PAs (NP PA)	N/A
	SHARE PC	# SRVC
	SHARE PC	NP PA
	SHARE PC	# PROV
	# SRVC	SHARE PC
	# SRVC	NP PA
	# SRVC	# PROV
	NP PA	# SRVC
	NP PA	SHARE PC
	NP PA	# PROV
	# PROV	# SRVC
	# PROV	SHARE PC
	# PROV	NP PA
Distance Interacted with Provider characteristics ($T_{ij} \cdot R_j$)	Distance (DIST)	N/A
	DIST	# SRVC
	DIST	# PROV
	DIST	SHARE PC
	DIST	NP PA
Distance Interacted with Patient Characteristics ($T_{ij} \cdot X_i$)	DIST	Sex
	DIST	Age
	DIST	Race
	DIST	Patient used either inpatient or outpatient services in 2009 (IP/OP)
	DIST	Patient used long term care services in 2009 (LTC)
	DIST	Patient has a history of a severe medical diagnosis (SEVERE)
	DIST	Patient has a history of a less severe medical diagnosis (MINOR)

Table 2.2 (Continued)

	SHARE PC	Sex
	SHARE PC	Race
	SHARE PC	Age
	SHARE PC	IP/OP
	SHARE PC	LTC
	SHARE PC	SEVERE
	SHARE PC	MINOR
	# SRVC	Sex
	# SRVC	Race
	# SRVC	Age
	# SRVC	IP/OP
	# SRVC	LTC
Provider Characteristics Interacted with Patient Characteristics ($R_j' \cdot \Gamma_1 \cdot X_i$)	# SRVC	SEVERE
	# SRVC	MINOR
	NP PA	Sex
	NP PA	Race
	NP PA	Age
	NP PA	IP/OP
	NP PA	LTC
	NP PA	SEVERE
	NP PA	MINOR
	# PROV	Sex
	# PROV	Race
	# PROV	Age
	# PROV	IP/OP
	# PROV	LTC
	# PROV	SEVERE
	# PROV	MINOR
Patient and Provider Match ($S_j' \cdot \Gamma_2 \cdot Z_i$)	Patient diagnosis code	Provider diagnosis code
	Patient procedure code	Provider procedure code

Notes: A “MINOR” diagnosis is defined by a history of cataracts, glaucoma, COPD, osteoporosis, or arthritis. A “SEVERE” diagnosis is defined by a history of Alzheimer’s disease, dementia, atrial fibrillation, congestive heart failure, ischemic heart disease, acute myocardial infarction, cancer (endometrial, breast, colorectal, lung, or prostate), diabetes, hip fracture, or stroke.

Table 2.3: Coefficient Estimates from Cardiology Logit Demand Model

Utility Input	Utility Coefficient	Utility Input	Utility Coefficient	Utility Input	Utility Coefficient
Distance	-0.19593 (0.00317)	Share Cardiologists*Female	-0.10447 (0.02118)	N Services*NP and/or PA	-0.00021 (0.00000)
N Services	0.00026 (0.00001)	Share Cardiologists*Age	-0.12501 (0.01521)	N Services*N Providers	0.00000 (0.00000)
Share Cardiologists	0.71948 (0.11711)	Share Cardiologists*White	0.26717 (0.03095)	NP and/or PA*Female	0.02706 (0.01319)
NP and/or PA	0.75802 (0.07436)	Share Cardiologists*IP/OP	-0.28763 (0.05889)	NP and/or PA*Age	-0.17019 (0.00940)
Match Diagnosis	25.81602 (1069.09700)	Share Cardiologists*LTC	-0.01160 (0.02218)	NP and/or PA*White	-0.09032 (0.01858)
Match Procedure	25.61170 (1022.54700)	Share Cardiologists*Severe DX History	0.53942 (0.04891)	NP and/or PA*IP/OP	-0.09191 (0.03573)
N Providers	-0.01732 (0.00105)	Share Cardiologists*Minor DX History	0.14308 (0.08721)	NP and/or PA*LTC	-0.01918 (0.01383)
Distance*Female	-0.00581 (0.00051)	Share Cardiologists*N Services	0.00000 (0.00000)	NP and/or PA*Severe DX History	0.28735 (0.03136)
Distance*Age	-0.01257 (0.00036)	Share Cardiologists*NP and/or PA	0.57981 (0.02674)	NP and/or PA*Minor DX History	-0.09439 (0.05332)
Distance*White	0.06943 (0.00116)	Share Cardiologists*N Providers	0.01809 (0.00080)	NP and/or PA*N Providers	0.01363 (0.00055)
Distance*IP/OP	0.02722 (0.00149)	N Services*Female	0.00000 (0.00000)	N Providers*Female	-0.00033 (0.00016)
Distance*LTC	0.00524 (0.00055)	N Services*Age	0.00002 (0.00000)	N Providers*Age	-0.00304 (0.00011)
Distance*Severe DX History	0.00880 (0.00135)	N Services*White	0.00003 (0.00000)	N Providers*White	-0.00388 (0.00025)
Distance*Minor DX History	0.00594 (0.00227)	N Services*IP/OP	-0.00004 (0.00000)	N Providers*IP/OP	0.00628 (0.00042)
Distance*N Services	0.00000 (0.00000)	N Services*LTC	-0.00002 (0.00000)	N Providers*LTC	0.00312 (0.00017)
Distance*Share Cardiologists	0.00187 (0.00016)	N Services*Severe DX History	-0.00001 (0.00000)	N Providers*Severe DX History	0.00137 (0.00040)

Table 2.3 (Continued)

Distance*NP and/or PA	-0.00048 (0.00012)	N Services*Minor DX History	0.00000 (0.00000)	N Providers*Minor DX History	-0.00005 (0.00066)
Distance*N Providers	0.00000 (0.00000)				
Observations: 28,065,128 Pseudo R2: 0.4436					

Notes: Standard errors in parentheses.

Table 2.4: Coefficient Estimates from Oncology Logit Demand Model

Utility Input	Utility Coefficient	Utility Input	Utility Coefficient	Utility Input	Utility Coefficient
Distance	-0.18280	Share Oncologists*Female	0.28510	N Services*NP and/or PA	0.00010
	(0.00640)		(0.03220)		(0.00000)
N Services	-0.00010	Share Oncologists*Age	0.13730	N Services*N Providers	0.00000
	(0.00000)		(0.02360)		(0.00000)
Share Oncologists	1.04400	Share Oncologists*White	0.21870	NP and/or PA*Female	-0.04970
	(0.19180)		(0.04600)		(0.02930)
NP and/or PA	0.42950	Share Oncologists*IP/OP	-0.30970	NP and/or PA*Age	-0.04030
	(0.17590)		(0.13460)		(0.02200)
Match Diagnosis	26.16610	Share Oncologists*LTC	-0.19980	NP and/or PA*White	0.28820
	(1099.52100)		(0.03460)		(0.04130)
Match Procedure	25.50770	Share Oncologists*Severe DX History	0.12470	NP and/or PA*IP/OP	-0.69500
	(1100.56800)		(0.06180)		(0.11290)
N Providers	0.06220	Share Oncologists*Minor DX History	0.31100	NP and/or PA*LTC	-0.44100
	(0.00190)		(0.11020)		(0.03240)
Distance*Female	-0.00210	Share Oncologists*N Services	0.00040	NP and/or PA*Severe DX History	0.41310
	(0.00100)		(0.00000)		(0.05670)
Distance*Age	-0.00800	Share Oncologists*NP and/or PA	-0.25130	NP and/or PA*Minor DX History	0.67940
	(0.00080)		(0.06920)		(0.10130)
Distance*White	0.05620	Share Oncologists*N Providers	-0.14420	NP and/or PA*N Providers	-0.06070
	(0.00210)		(0.00320)		(0.00110)
Distance*IP/OP	0.02900	N Services*Female	0.00000	N Providers*Female	0.00150
	(0.00430)		(0.00000)		(0.00030)
Distance*LTC	-0.01230	N Services*Age	0.00000	N Providers*Age	0.00060
	(0.00120)		(0.00000)		(0.00020)
Distance*Severe DX History	-0.01810	N Services*White	0.00000	N Providers*White	-0.00050
	(0.00190)		(0.00000)		(0.00040)
Distance*Minor DX History	0.01940	N Services*IP/OP	0.00000	N Providers*IP/OP	-0.00010
	(0.00420)		(0.00000)		(0.00120)
Distance*N Services	0.00000	N Services*LTC	0.00000	N Providers*LTC	-0.00010
	(0.00000)		(0.00000)		(0.00030)
Distance*Share Oncologists	-0.00500	N Services*Severe DX History	0.00000	N Providers*Severe DX History	-0.00840
	(0.00030)		(0.00000)		(0.00060)

Table 2.4 (Continued)

Distance*NP and/or PA	-0.00560 (0.00040)	N Services*Minor DX History	0.00000 (0.00000)	N Providers*Minor DX History	-0.00450 (0.00100)
Distance*N Providers	0.00010 (0.00000)				
Observations: 5,558,144 Pseudo R2: 0.5483					

Notes: Standard errors in parentheses.

Table 2.5: Coefficient Estimates from Orthopedic Logit Demand Model

Utility Input	Utility Coefficient	Utility Input	Utility Coefficient	Utility Input	Utility Coefficient
Distance	-0.16600	Share Orthopedists*Female	0.08820	N Services*NP and/or PA	-0.00050
	(0.00760)		(0.04720)		(0.00000)
N Services	0.00050	Share Orthopedists*Age	0.23660	N Services*N Providers	0.00000
	(0.00000)		(0.03150)		(0.00000)
Share Orthopedists	-0.69940	Share Orthopedists*White	0.20910	NP and/or PA*Female	-0.06680
	(0.27470)		(0.07650)		(0.02860)
NP and/or PA	-0.94860	Share Orthopedists*IP/OP	-0.13920	NP and/or PA*Age	0.15400
	(0.27470)		(0.09630)		(0.01950)
Match Diagnosis	25.50820	Share Orthopedists*LTC	-0.00900	NP and/or PA*White	-0.10440
	(967.44260)		(0.04940)		(0.04740)
Match Procedure	24.49200	Share Orthopedists*Severe DX History	-0.30250	NP and/or PA*IP/OP	-0.07600
	(998.77620)		(0.05340)		(0.05690)
N Providers	-0.08760	Share Orthopedists*Minor DX History	-0.17470	NP and/or PA*LTC	-0.00830
	(0.00450)		(0.24710)		(0.03000)
Distance*Female	-0.01550	Share Orthopedists*N Services	-0.00020	NP and/or PA*Severe DX History	-0.18180
	(0.00120)		(0.00000)		(0.03190)
Distance*Age	-0.00800	Share Orthopedists*NP and/or PA	2.11680	NP and/or PA*Minor DX History	-0.05200
	(0.00080)		(0.05360)		(0.14160)
Distance*White	0.04210	Share Orthopedists*N Providers	0.10680	NP and/or PA*N Providers	0.07450
	(0.00280)		(0.00240)		(0.00240)
Distance*IP/OP	0.01890	N Services*Female	0.00000	N Providers*Female	-0.00380
	(0.00250)		(0.00000)		(0.00070)
Distance*LTC	0.00590	N Services*Age	0.00000	N Providers*Age	-0.00530
	(0.00120)		(0.00000)		(0.00050)
Distance*Severe DX History	-0.00470	N Services*White	0.00000	N Providers*White	0.00320
	(0.00130)		(0.00000)		(0.00130)
Distance*Minor DX History	0.00360	N Services*IP/OP	-0.00010	N Providers*IP/OP	0.01370
	(0.00660)		(0.00000)		(0.00140)
Distance*N Services	0.00000	N Services*LTC	0.00000	N Providers*LTC	0.00160
	(0.00000)		(0.00000)		(0.00070)

Table 2.5 (Continued)

Distance*Share Orthopedists	0.00160 (0.00030)	N Services*Severe DX History	0.00000 (0.00000)	N Providers*Severe DX History	-0.00400 (0.00080)
Distance*NP and/or PA	0.00060 (0.00020)	N Services*Minor DX History	0.00010 (0.00000)	N Providers*Minor DX History	-0.00920 (0.00330)
Distance*N Providers	0.00000 (0.00000)				
Observations: 7,691,004					
Pseudo R2: 0.5601					

Notes: Standard errors in parentheses.

The underlying utility parameter estimates are then used to generate a WTP for the inclusion of each practice in a network. The WTP measure reflects the populations WTP for a specific group practice in "logit utils." The relative scale of the WTP measure is thus meaningless. The importance of the measure is that the "logit utils" can be converted into a price. Recalling the assumption that utils are related to price through the constant γ allows for this transformation. Tables 2.6, 2.7, and 2.8 contain descriptive statistics and WTP estimates for the three physician specialties in a large metropolitan area.

Table 2.6: Cardiology Practices and WTP Estimates

ID	N Providers	Share Cardiologists	NP/PA	$\frac{WTP}{RVU}$	$Price = \frac{\$}{RVU}$	$\frac{RVU}{Q}$ Medicare	$\frac{RVU}{Q}$ Private
1	2	1.00	0	0.57	34.43	2.91	3.37
2	2	1.00	0	0.27	31.15	8.63	6.06
3	1	1.00	0	0.83	31.06	1.13	1.80
4	1	1.00	0	0.48	30.27	0.94	0.81
5	1	1.00	0	0.12	32.70	2.60	3.61
6	1	1.00	0	0.52	44.67	1.30	2.95
7	9	1.00	0	0.22	29.67	3.70	5.34
8	1	1.00	0	0.26	36.79	4.07	3.60
9	1	1.00	0	0.09	18.35	3.02	3.01
10	1	1.00	0	0.19	34.18	1.86	1.73
11	4	1.00	0	0.01	19.93	9.54	4.77
12	1	1.00	0	0.49	39.09	3.50	1.85
13	4	1.00	0	0.60	38.04	2.07	2.40
14	5	1.00	0	0.16	38.13	5.68	3.67
15	3	1.00	0	0.07	30.39	8.95	9.72
16	3	1.00	0	0.10	30.09	4.36	4.39
17	4	1.00	0	0.28	33.98	5.30	5.33
18	6	0.17	0	0.39	43.36	1.89	1.99
19	4	1.00	0	0.24	30.15	4.54	5.13
20	3	0.33	0	0.09	30.40	4.68	5.79
21	3	0.67	1	0.20	40.27	5.95	5.17
22	1	1.00	0	0.15	32.70	2.70	3.61
23	13	0.15	0	0.05	31.40	2.33	2.31
24	9	1.00	0	0.35	31.69	3.50	5.04
25	6	0.83	0	0.13	32.93	4.89	4.05
26	3	1.00	0	0.19	37.92	5.73	5.05

Source: Author's estimations.

Table 2.7: Oncology Practices and WTP Estimates

ID	N Providers	Share Cardiologists	NP/PA	$\frac{WTP}{RVU}$	$Price = \frac{\$}{RVU}$	$\frac{RVU}{Q}$ Medicare	$\frac{RVU}{Q}$ Private
1	2	1.00	0	0.33	42.31	6.02	7.34
2	1	1.00	0	0.34	19.25	7.36	7.70
3	2	1.00	0	0.14	34.60	6.61	5.06
4	3	1.00	0	0.08	18.73	4.61	4.30
5	4	1.00	0	0.29	34.52	2.11	2.62
6	4	1.00	0	1.27	38.25	2.37	1.69
7	1	1.00	0	0.48	38.05	2.16	2.45
8	2	1.00	0	0.82	39.81	1.70	2.06
9	1	1.00	0	0.66	36.40	1.87	2.76
10	9	1.00	0	0.56	39.16	1.92	1.72
11	8	1.00	0	0.64	37.11	1.82	1.55
12	9	1.00	0	0.58	36.67	1.83	2.41
13	2	1.00	0	0.20	41.07	6.81	6.61
14	6	0.67	1	0.37	39.35	2.00	2.16
15	2	1.00	0	0.40	38.82	1.95	1.88
16	4	0.75	1	0.56	37.17	1.66	2.51
17	5	0.80	1	0.73	50.64	2.02	2.00
18	2	1.00	0	0.15	17.27	5.36	5.30

Source: Author's estimations.

Table 2.8: Orthopedic Practices and WTP Estimates

ID	N Providers	Share Cardiologists	NP/PA	$\frac{WTP}{RVU}$	$Price = \frac{\$}{RVU}$	$\frac{RVU}{Q}$ Medicare	$\frac{RVU}{Q}$ Private
1	7	1.00	0	0.75	46.94	2.00	3.46
2	2	1.00	0	0.25	36.73	4.14	3.42
3	3	0.67	0	0.30	35.17	3.75	3.86
4	4	1.00	0	0.97	55.09	2.92	3.58
5	4	0.50	0	0.42	38.53	2.58	3.56
6	3	1.00	0	0.28	41.32	3.45	3.07
7	7	0.43	1	0.15	36.67	4.24	5.35
8	2	0.50	0	0.22	31.51	4.09	3.92
9	1	1.00	0	0.23	37.52	2.02	2.46
10	2	1.00	0	0.17	37.97	2.95	2.94
11	9	1.00	0	0.25	43.14	3.14	2.49
12	3	1.00	0	0.09	34.48	6.23	5.24
13	3	1.00	0	0.60	36.64	2.23	2.09
14	3	1.00	0	0.51	38.45	2.78	2.61
15	7	0.57	0	0.26	36.00	5.86	5.55
16	6	1.00	0	0.39	48.04	3.21	3.64
17	2	1.00	0	0.05	36.50	4.88	5.34
18	2	1.00	0	0.31	36.38	3.59	2.86
19	6	0.83	1	0.27	36.88	3.16	3.71
20	2	1.00	0	0.23	37.92	2.76	3.01
21	9	0.78	0	0.26	37.90	3.20	3.05
22	3	0.33	0	0.36	46.32	2.61	2.86
23	18	0.72	1	0.24	34.79	4.56	3.67
24	8	1.00	0	0.24	36.20	3.55	3.35
25	16	0.88	0	0.32	35.37	3.52	3.49
26	2	1.00	0	0.19	33.49	5.57	4.79
27	10	0.60	1	0.22	43.47	4.38	3.63
28	18	0.06	1	0.31	38.67	2.30	1.90

Source: Author's estimations.

Table 2.9 displays the estimations of the bargaining parameter for each specialty by service intensity. Figure 2.1 shows scatterplots of the relationship between normalized WTP and price for each of the three specialties. The rows delineate the specialty and the columns investigate the potential for market segmentation within physician specialties by average service intensity. The average service intensity is calculated for each practice group by calculating the average RVUs per service for both Medicare services and private services. The sample is then limited by first removing the top 5% and the bottom 5% of service intensity and looking at market power in the middle 90th percentile of service intensity. This process is repeated for the middle 80th percentile as well. Removing the tails of service intensity allows me to analyze a source of potential market segmentation. Specifically, removing service intensity outliers generates a sample of practices that are more likely to compete with each other. In fact, the strongest evidence of physician market power in all markets comes from examining the middle 80th percentile of service intensity. As to be expected, the results are sensitive to the inclusion of these outliers since practices that perform high intensity services may be competing in a separate product market. Limiting the market to physician practices performing similar services is an assurance that I am analyzing practices that are competing in the same product market.

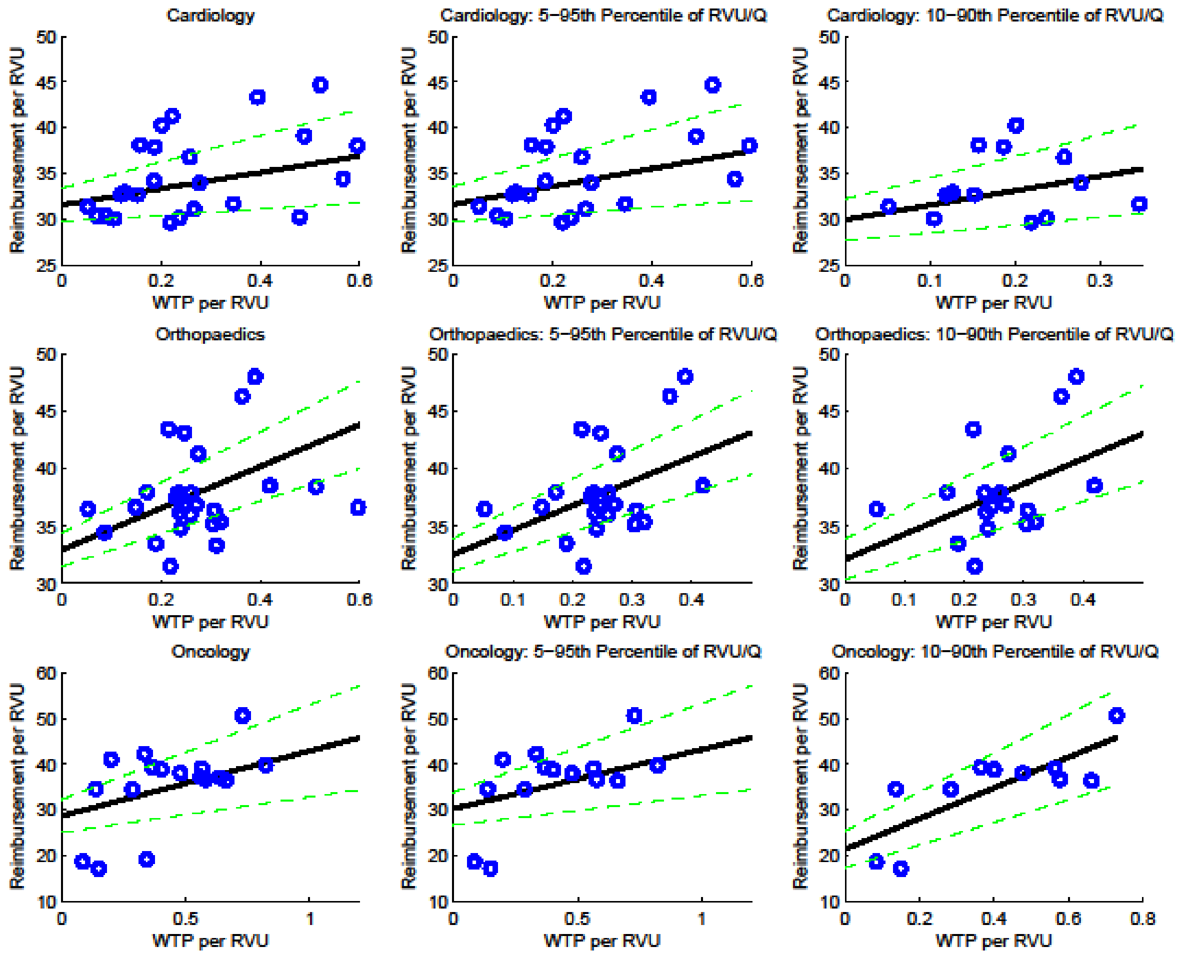


Figure 2.1: Scatter Plot of $\frac{WTP}{RVU}$ *and Price*

Excluded from the scatterplots, are hospital based practices, practices that perform very few Medicare and private services in the dataset (fewer than 100 services), practices with less than 10% of their providers being in the relevant specialty, as well as practices that performed significantly different services for Medicare verses private patients.[28] [29]

Table 2.9: Estimates of the Bargaining Parameter Dependent Variable: Price per RVU

Specialty	Market	N	α	β
Cardiology	All	26	31.58	8.85
			(1.83)***	(5.41)
	5-95pct	24	31.65	9.70
			(1.94)***	(5.75)
	10-90pct	18	29.97	15.80
			(2.25)***	(7.51)**
Orthopedics	All	28	32.93	18.18
			(1.45)***	(3.92)***
	5-95pct	25	32.53	21.27
			(1.45)***	(4.36)***
	10-90pct	20	32.11	21.92
			(1.76)***	(4.90)***
Oncology	All	18	28.73	14.20
			(3.60)***	(6.48)**
	5-95pct	15	30.30	12.91
			(3.61)***	(6.43)*
	10-90pct	11	21.43	33.46
			(4.01)***	(8.82)***

Notes: Standard errors in brackets. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Analyzing the middle 80th percentile of the service intensity distribution yields results indicating substantial market power for both physicians and insurers in all three specialties. The estimates of both the intercept and the slope parameters in all regressions for this group were positive and statistically significant. It is important to note that these results are sensitive

[28] Practices in which the difference between average RVU per service for Medicare patients versus private patients was greater than 1.5 times the standard deviation of the difference were removed.
[29] The results presented here are extremely robust to varying the levels of these restrictions. The restrictions here were chosen to balance the validity of the price index and WTP measure with the estimating power of the OLS price regression.

to including practices in the tails of the service intensity distribution, but the changes in estimates are relatively minor. The changes in my estimates when including practices that provide extremely low or extremely high level of service intensity is consistent with the notion that these outlier practices provide a different set of services than most of the practices in the data. The product market here is the market in which physicians compete over patients to provide similar services. Practices providing very high or very low intensity services are not competing over the same types of patients and thus should not be included in the relevant product market. The results including all practices, as well as the middle 90th percentile of the distribution are included as robustness checks.

2.6 Conclusions

The application of the option demand model to hospitals has been shown to be a reliable method for assessing market power in hospital inpatient markets, and this research is the first step to validating the model’s use in assessing physician practice market power. The results from the option demand model applied to physician group practices indicate the existence of market power in the specialty physician group practice market in the large CBSA chosen to conduct this analysis. While these results are based on only one CBSA, the results are of greater interest to future applications of the option demand model to physician markets.

However, the methods used in this paper are not without limitations. First, it is implicitly assumed in this study that Medicare Fee-for-Service (FFS) beneficiaries select physicians based on similar criteria as younger privately insured patients. This assumption is violated if there is a self-selection problem with respect to Medicare enrollees selecting to enroll in Medicare FFS verses Medicare Advantage (MA), enrollees in the latter have opted into a system that more closely resembles private insurance with access to physicians through a network. Medicare FFS enrollees also have a greater freedom of choice when selecting physicians, and are not subject to out-of-network charges (financial steering) that patients insured through the private sector may encounter. Second, while this study is the first to use actual transaction price data to infer physician market power, the price data is available for only 62% of the private insurance claims in the FAIR Health database. To the extent that these claims do not constitute a representative sample of insurers, the data may not accurately reflect the prices paid for primary care services in the analysis market. Lastly, this study shows the existence of physician market power in only one geographic area. Future work should apply these methods to other geographic areas. Despite these limitations, this analysis has made the assessment of market power in physician markets feasible and more complete than has been previously implemented.

REFERENCES

Akosa, A.Y., M.S. Gaynor, and W.B. Vogt (2009). Evaluating the Performance of Merger Simulation: Evidence from the Hospital Market in California. *Carnegie Mellon Working Paper*.

American Bar Association, (ABA) (2003). Health Care Mergers and Acquisitions Handbook. Chicago: ABA Publishing.

Berenson, R.A., P.B. Ginsburg, and N. Kemper (2010). Unchecked Provider Clout In California Foreshadows Challenges To Health Reform. *Health Affairs*, 29(4):1-7.

Berry, S., J. Levinsohn, and A. Pakes (2004). Differentiated Products Demand Systems from a Combination of Micro and Macro Data: The New Car Market. *Journal of Political Economy*, 112(1):68-105.

Burns, L.R. and D.R. Wholey (1992). The Impact of Physician Characteristics in Conditional Choice Models for Hospital Care. *Journal of Health Economics*, 11(1):43-62.

Capps, C. (2012). Economic Analysis of Hospital Mergers in the 21st Century. Antitrust in Healthcare Conference.

Capps, C., D. Dranove, S. Greenstein, and M. Satterthwaite (2001). The Silent Majority Fallacy of the Elzinga-Hogarty Criteria: A Critique and New Approach to Analyzing Hospital Mergers. *NBER Working Paper 8216*.

Capps, C., D. Dranove, and M. Satterthwaite (2003). Competition and Market Power in Option Demand Markets. *RAND Journal of Economics*, 34(4):737-763.

Centers for Medicare & Medicaid Services, (CMS) (2010). Fee-for-Service Medicare Quality and Resource Use Report. Accessed at: http://www.google.com/url?sa=t\&rct=j\&q=fee-for-service\%20medicare\%20quality\%20and\%20resource\%20use\%20report\&source=web\&cd=1\&ved=0CC0QFjAA\&url=http\%3\%2F\%2Fwww.cms.gov\%2FPhysicianFeedbackProgram\%2FDownloads\%2FQRUR_Physicians.pdf\&ei=AQh9T-3ONYX88gSVkdmSDQ\&usg=AFQjCNF__ih5pCxU7CMw209Tg_0c1WUuYg\&cad=rja

Centers for Medicare & Medicaid Services, (CMS) (2011). Physician Group Practice Transition Demonstration Design Overview. Accessed at: https://www.cms.gov/Medicare/Demonstration-Projects/DemoProjectsEvalRpts/downloads//PGP_Transition_Design_Summary.pdf

Cohen, M.A. and H.L. Lee (1985). The Determinants of Spatial Distribution of Hospital Utilization in a Region. *Medical Care*, 23(1):27-38.

Cooper, R. and T.R. Kramer (2008). RBRVS Costing: The Inaccurate Wolf in Expensive Sheep's Clothing. *Journal of Health Care Finance*, 34(3):6-18.

Dove, H.G. (1994). Use of the resource-based relative value scale for private insurers. *Health Affairs*, 13(5):193-201.

Dranove, D., M. Shanley, and W. White (1993). Price and Concentration in Hospital Markets: The Switch from Patient Driven to Payer Driven Competition. *Journal of Law and Economics*, 36:179-204.

Dranove, D. and A. Sfekas (2009). The Revolution in Health Care Antitrust: New Methods and Provocative Implications. *The Milbank Quarterly*, 87(3):607-632.

Dranove, D., M. Shanley, and C.J. Simon (1992). Is Hospital Competition Wasteful? *RAND Journal of Economics*, 23:247-262.

Elzinga, K. and A. Swisher (Forthcoming). Limits of the Elzinga-Hogarty Test in Hospital Mergers: the Evanston Case. *International Journal of the Economics of Business*.

Farrell, J., D.J. Balan, and K. Brand (2011). Economics at the FTC: Hospital Mergers, Authorized Generic Drugs, and Consumer Credit Markets.

Federal Trade Commission, and Department of Justice (2004). Improving Health Care: A Dose of Competition. Accessed at: www.usdoj.gov/atr/public/health_care/204694.htm#toc

Federal Trade Commission, and Department of Justice (2010). Horizontal Merger Guidelines.

Fournier, G.M. and Y. Gai (2007). What does Willingness-to-Pay Reveal About Hospital Market Power in Merger Cases? *Working Paper*.

Gaynor, M., S.A. Kleiner, and W.B. Vogt (2012). A structural Approach to Market Definition with an Application to the Hospital Industry. *Working Paper*.

Gaynor, M. and R.J. Town (2011). Competition in Health Care Markets. *NBER Working Paper 17208*.

Gaynor, M. and W.B. Vogt (2000). Antitrust and Competition in Health Care Markets. *In A.J. Culyer and J.P. Newhouse, eds. Handbook of Health Economics*, 1B New York: North Holland (Chapter 27).

Gaynor, M. and W.B. Vogt (2003). Competition Among Hospitals. *RAND Journal of Economics*, 34(4):764-785.

Ginsburg, P. (2010). Wide Variation in Hospital and Physician Payment Rates Evidence of Provider Market Power. *Center for Studying Health System Change*.

Grennan, M. (forthcoming). Price Discrimination and Bargaining: Empirical Evidence from Medical Devices. *American Economic Review*.

Gruber, J. (1994). The Effect of Price Shopping in Medical Markets: Hospital Responses to PPOs in California. *Journal of Health Economics*, 38:183-212.

Irving Levin Associates, Inc. (2007). Deals and Dealmakers: The Health Care M&A Year in Review. Norwalk, CT, 12th Edition. Accessed at: http://www.levinassociates.com/compallconfirm?sid=6050

Irving Levin Associates, Inc. (2008). Deals and Dealmakers: The Health Care M&A Year in Review. Norwalk, CT, 13th Edition. Accessed at: http://www.levinassociates.com/compallconfirm?sid=6050

Irving Levin Associates, Inc. (2009). Deals and Dealmakers: The Health Care M&A Year in Review. Norwalk, CT, 14th Edition. Accessed at: http://www.levinassociates.com/compallconfirm?sid=6050

Irving Levin Associates, Inc. (2010). Deals and Dealmakers: The Health Care M&A Year in Review. Norwalk, CT, 15th Edition. Accessed at: http://www.levinassociates.com/compallconfirm?sid=6050

Kaiser Family Foundation, (KFF) (2005). Trends and Indicators in the Changing Health Care Marketplace. Accessed at: http://www.kff.org/insurance/7031/print-sec5.cfm

Lynk, W.J. (1995a). Nonprofit Hospital Mergers and the Exercise of Market Power. *Journal of Law and Economics*, 38:437-461.

Martin, A.B., D. Lassman, B. Washington, A. Catlin, and the National Health Expenditure Accounts Team Growth (2012). US Health Spending Remained Slow In 2010; Health Share Of Gross Domestic Product Was Unchanged From 2009. *Health Affairs*, 31(1):208-219.

Mayer, J.D. (1983). The Distance Behavior of Hospital Patients: A Disaggregated Analysis. *Social Science & Medicine*, 17(12):819-827.

Pham, H.H., D. Schrag, A.S. O'Malley, B. Wu, and P.B. Bach (2007). Care Patterns in Medicare and their Implications for Pay for Performance. *New England Journal of Medicine*, 356(11):1130-1139.

Robinson, J.C. and H. Luft (1985). The Impact of Hospital Market Structure on Patient Volume, Average Length of Stay, and the Cost of Care. *Journal of Health Economics*, 4:333-356.

Romeo, A.A., J.L. Wagner, and R.H. Lee (1984). Prospective Reimbursement and the Diffusion of New Technologies in Hospitals. *Journal of Health Economics*, 3:1-24.

Schneider, J., P. Li, D. Klepser, N. Peterson, T. Brown, and R. Scheffler (2008). The Effect of Physician and Health Plan Market Concentration on Prices in Commercial Health Insurance Markets. *International Journal of Health Care Finance and Economics*, 8:13-26.

Town, R. and G. Vistnes (2001). Hospital Competition in HMO Networks. *Journal of Health Economics*, 20(5):733-753.

Varkevisser, M. and S. van der Geest (2006). Why do Patients Bypass the Nearest Hospital? An Empirical Analysis for Orthopedics Care and Neurosurgery in the Netherlands. *Working Paper*.

CHAPTER 3

THE IMPORTANCE OF VALUING HEALTH INSURANCE WHEN MEASURING AND ACCOUNTING FOR CHANGES IN THE INCOME OF WORKING AGED PEOPLE WITH AND WITHOUT DISABILITIES

3.1 Introduction

There is considerable debate over the importance of including the value of employer and government provided health insurance in income measures that attempt to capture the ability of households to consume good and services or to save for future periods (See for example: Burkhauser, Larrimore & Simon, 2013; and Aaron & Burtless, 2014). While employer or government provided health insurance does not have the explicit tradable value of cash wages or cash government transfers, it is possible to put a cash value on it for the purpose of measuring yearly income. In-kind compensation in the form of employer provided health insurance and in-kind government transfers in the form of Medicare and Medicaid directly provide access to health insurance and while these benefits cannot be traded, they have some value to those who receive it. Effectively valuing the consumption value of health insurance at zero by excluding it from income measures clearly undervalues it, and will do so move over time if its value increases as a share of wage compensation or the mix of government transfers provided households.

Including the value of health insurance in an income measure theoretically moves the measure toward a definition of access to economic resources by adding up all expenditures on consumption. This theoretical point was made by the Congressional Budget Office (CBO) (2012, 2013) in their justification for including the market value of health insurance in their income measure beginning in 2012. This essay will measure the impact of including the market value of health insurance on levels and trends in the median income of working age people (aged 18-64) with and without disabilities.

Past measures of income that excluded the value of employer and government provided health insurance found a rising gap in the level of median income of these those without and those with disabilities. This was especially the case when only market income was included. While the inclusion of in-cash government transfers narrowed the gap somewhat, it still continued to grow over time. This finding is reversed when the market value of health insurance is included.

This essay also shows what accounts for changes in this fuller measure of the median income of working age people with and without disabilities over the last three business cycles from 1983-2011, using a shift share analysis. Shift share analysis decomposes the growth in income into individual contributions from changes in demographics and source incomes.

This analysis uses the public use March Current Population Survey (CPS), the most common data source researchers' use to measure levels and long term trends in United States income and its distribution. This essay compares four alternative measures of income using these data. The first is market income (all private sources of cash income). Piketty & Saez (2003) and others in the income inequality literature use this measure of income but do so primarily with income tax records data (See: Atkinson, Piketty & Saez, 2011, for a review of this literature). The second is market and government income (all private and public sources of cash income). This was the most commonly used income measure through the early 2000s (See: Atkinson & Brandolini, 2001; and Gottschalk & Smeeding, 1997, for reviews of this literature). It continues to be used by the Census Bureau (U.S. Census Bureau, various years) and by those tracking the resources available to those with and without disability (See for example: Houtenville *et al.,* 2009; Burkhauser & Daly, 2011; and Stapleton, 2011). The third is disposable income (market and government income plus the value of in-kind transfers except employer and government provided health insurance minus taxes). The fourth is disposable income plus health insurance (disposable income plus the insurance value of employer and government provided health insurance) used by CBO since 2012 and by Burkhauser, Larrimore, & Simon (2012), Armour, Burkhauser, & Larrimore (2013, forthcoming), and Aaron & Burtless (2014). It is the fullest of the four yearly measures of the flow of resources available to individuals and their households.[30]

Including the value of health insurance as income recognizes the policy shift of the United States government from providing in-cash transfers to providing more in-kind transfers. This is especially true for health insurance with Medicare and Medicaid, and even more recently the Affordable care Act of 2010 (ACA). The ACA both expands Medicaid and provides substantial subsidies for the purchase of health insurance through government run exchanges. The ACA along with the substantial rise in the cost of health insurance in both government and employer subsidized coverage underscores the importance of including this in-kind benefit in any measure attempting to capture access to material resources.

This essay confirms findings by others who include health insurance in their measure of income in that doing so substantially increases median income and its growth for the population as a whole. This continues to be the case, but to a lesser degree for the working age population and much more for the working age population with disabilities. While the income gap between those with and without disabilities increases over time using the first three

[30] Some would argue, based on a Haig-Simons principal of income, that capital gains should also be included. The CBO includes realized capital gains in its measure of income as do some researchers in the top income literature. However, numerous researchers have pointed out that accrued capital gains is more consistent with the Haig-Simons measure of income (Auerbach, 1989; Roine & Waldenstrom, 2012; and Armour, Burkhauser, & Larrimore 2013, forthcoming). Furthermore, Armour *et al.* (2013) demonstrate that taxable realized capital gains is not a very accurate measure of accrued capital gains to capture levels and trends in top income.

measures, it falls when the value of health insurance is included. More generally when the insurance value of health insurance is included, the share of people with disabilities in the bottom quintile of the working age population falls. Decisions to include or ignore the value of health insurance dramatically affect the level and the trend in the median income of the working age population with and without disabilities and the demographic make-up of the bottom part of the income distribution.

This essay uses four definitions of income, some of which may be better classified as material resources. Income definitions 3 and 4 include in-kind benefits, this essay recognizes that these measures include more than just cash income, and for simplicity in exposition, all measures will be referred to as “income.” Using the fullest measure of income in a shift share analyses, this essay shows that between 1983 and 2011, median household income of working age people with disabilities increased by 50.85 percent compared 31.46 percent for working age people without disabilities. Growth in the labor earnings of others family members is the single most important source of this increase followed by the growth in own labor earnings for working age people without disabilities—both market income sources. In contrast, growth in the insurance value of Medicare and Medicaid benefits for those receiving either Social Security Disability Insurance (SSDI) or Supplemental Security Income (SSI) is by far the single most important source of income for working age people without disabilities, with the labor earnings of other household members a distant second. However the majority of this increase occurred between 1993 and 2004.

3.2 Review of the Literature

Market income (definition 1) does not fully capture the resources available to individuals. For instance, the United States provides categorical cash support to low income single mothers with children via the Temporary Assistance for Needy Families program (TANF) as well as access to in-kind support via government provided Food Stamps (SNAP). Hence the traditional CPS-based income literature includes market and government income (income definition 2), but has only recently included some in-kind transfers and also accounted for taxes (subtracting federal and state taxes but adding the Earned Income Tax Credit and other tax based credits)—disposable income (income definition 3). It is only very recently that researchers have included the value of employer and government provided health insurance in their income measures—disposable income plus health insurance (income definition 4) and this continues to be controversial due to the debate over whether income or consumption is a preferable measure of economic wellbeing.

Past analyses of the income of working age people with disabilities using a market and government cash income measure have found that, despite significant increases in SSDI/SSI program enrollment and costs, their income has steadily declined relative to working age people without disabilities (Burkhauser *et al.*, 2009; Burkhauser & Daly, 2011; Stapleton, 2011; and Weathers & Wittenburg, 2009). However, a growing fraction of persons with disabilities are not only receiving cash support through SSI/DI programs, but also access to Medicare and Medicaid. This essay shows that doing so matters and that it is appropriate to include these resources within a fuller measure of income.

3.3 Inclusion of the Market Value of Health Insurance as Income

Until recently, researchers did not include the insurance value of health insurance in measures of income (See: Atkinson & Brandolini, 2001; and Gottschalk & Smeeding, 1997, for reviews of this literature). The Census Bureau (U.S. Census Bureau, various years) still excludes the value of health insurance in its measures of median market and government income (definition 2) and gives it no value for those in poverty in its fuller measures of income. Burtless (2010) notes the importance of including government income in the analysis of income trends, especially over recessions. Tax policies and government in-cash and in-kind benefits are an important component of many households' incomes. Aaron & Burtless (2014) include the market value of health insurance in their measure of income (disposable income plus health insurance) to analyze the potential effects of the Affordable Care Act on income inequality. The Congressional Budget Office (2012, 2013) also uses a disposable income plus health insurance measure of income to analyze income inequality. The Congressional Budget Office (2013) finds that income inequality has been growing rapidly at the top one percent of the income distribution while income inequality for those below the 99^{th} percentile has remained largely unchanged over the past 30 years. Burkhauser, Larrimore, & Simon (2013) include the market value of health insurance in their measure of income (disposable income plus health insurance) and find that income inequality decreases relative to a measure of disposable income alone. Additionally Burkhauser, Larrimore, & Simon (2013) find that the benefit from the expansion of health insurance under the Affordable Care Act would be accrued mostly by the bottom 30^{th} percentile of the income distribution. This result reflects the fact that the market value of government provided health insurance has been growing faster than the market value of employer provided health insurance.

Armour, Burkhauser, & Larrimore (2013, forthcoming) include the value of health insurance in their tables comparing trend results using their preferred measure of income (disposable income plus health insurance) with those of CBO (2013) and show that it is the CBO's inclusion of taxable realized capital gains in their preferred measure of income (disposable income plus health insurance plus taxable realized capital gains) rather than other sources of income that accounts for differences in the two sets of income trend results.

A full measure of the flow of economic resources to a household should include not only cash resources, but also access to goods and services such as housing, food and health care. Hence the market value of these goods and services should be included in any measure of their economic resources, regardless of whether access to these services is subsidized by the government or one's employer. An issue commonly confused with the including the value of health insurance as income is that individuals may not value in-kind benefits at their market value. This is reflected in the way the Census Bureau censors the fungible value of Medicare and Medicaid at zero for persons who fall below a specific income threshold. Because this essay attempts to measure the flow of resources to a household and not the individual valuation of the flow of resources, this issue is of no concern for this essay.

This paper does not attempt to disentangle individuals' idiosyncratic valuation of subsidized goods and services (e.g., Medicaid, SNAP (food stamps), housing subsidies), but instead measure the overall market value of earned income and subsidized goods and services. One concern, sometimes confounded with including the value of health insurance as income, is whether increases in the price of health insurance reflect medical inflation, with individuals receiving the same level of health care at a higher cost, or improvements in the quality of health benefits. The rising cost of health care affects all U.S. residents who desire to access medical services, independent of insurance status. The issue of why health care costs are rising is separate from the market valuation health insurance. Persons receiving employer sponsored health insurance or publicly sponsored health insurance do not pay the full market value because employers or the government subsidize the benefit (similar to SNAP or housing subsidies). Therefore, individuals receiving public health coverage who are in poverty may not value their public health insurance benefit at the full market value (cost to the government of providing the health benefit), but without the benefit they would be left with the choice of purchasing insurance on their own in the private market or going uninsured. Therefore, the market value of health insurance is a very important measure that directly affects economic wellbeing. As such, the subsidized market value of health insurance from both private and public sources should be included in any measure of economic wellbeing.

3.4 Methods

3.4.1 Introduction

The goal of this analysis is to assess trends in the economic resources available to working age people with and without disabilities over the past three decades using a more encompassing resource definition that includes the market value of employer and government provided health insurance. These trends are compared to the three alternative and less comprehensive income measures discussed above. Including the market value of health insurance in the fourth and fullest measure of income results in substantially different level and trends in median income from those found in the previous literature comparing the income of those with and without disabilities.

3.4.2 Data

This essay uses CPS data for income years 1980 to 2012 supplemented with cell-means for top-coded incomes from Larrimore *et al.* (2008) to analyze income trends between persons with and without disabilities. CPS data was, and continues to be, the most common data source researchers' use to measure trends in income and income inequality in general (for example, see DeNavas-Walt, Proctor, & Smith 2008, 2013; Gottschalk & Danziger, 2005; Daly & Valetta, 2006; Blank, 2011), and the employment and economic resources of working aged people with disabilities (for example, see Acemoglu & Angrist, 2001; Autor & Duggan, 2003, 2006; Bound & Waidmann, 1992, 2002; Burkhauser, Daly, & Houtenville, 2001; Burkhauser *et al.*, 2002; Daly & Burkhauser, 2003; Houtenville & Burkhauser, 2005; Hotchkiss, 2003, 2004; Jolls & Prescott, 2005, Burkhauser & Daly, 2011).

3.4.3 Identification of Working Aged Persons with Disabilities

The CPS is the only data set that provides consistent information on the economic resources of persons with disabilities since 1981 (income year 1980). We focus on working age (18 to 64) people who report having a work limiting condition.[31] Researchers should be cautious using any self-reported measure. Fortunately, the economics literature has specifically addressed the use of this work activity question as a proxy for disability status in the CPS. Benita-Silva *et al.* (2004) find that self-reported work limitation responses are an unbiased indicator of SSDI eligibility decisions and Stern (1989) finds that the measure is close to exogenous. Bound & Burkhauser (1999) find that the self-reported measure identifies populations with substantial differences in health status. Burkhauser *et al.* (2002) argue that the CPS can be reliably used to monitor trends in the outcomes of those with disabilities using the self-reported work limitation indicator.

3.4.4 Definition of Income

As discussed above this essay uses four income definitions that are increasingly more all-encompassing. Market income includes cash income from private sources. Market and government income includes cash income from private and government sources. Disposable income includes cash income from private sources and government sources plus some in-kind transfers (SNAP, housing subsidies, and school lunches) plus tax credits minus federal and state income taxes. Disposable income plus health insurance includes disposable income plus the full cash value of employer sponsored health insurance and government provided (Medicare and Medicaid) health insurance.

[31] The specific question asked to respondents is whether or not a person has "a health problem or disability which prevents work or which limits the kind or amount of work."

Market and government income has been the main definition used in prior income trend analyses (for example, see Gottschalk & Danziger, 2005; Daly & Valetta, 2006; Blank, 2011). Disposable income is the preferred measure in EU and OECD studies. Disposable income plus health insurance has been used to analyze income trends and inequality more recently in the literature (for example, see Aaron & Burtless, 2014; Congressional Budget Office, 2012, 2013; Burkhauser, Larrimore, & Simon, 2013; Armour, Burkhauser, & Larrimore 2013, forthcoming; Sommers & Oellerich, 2013).

The Census Bureau imputes the value of SNAP (food stamps), subsidized housing, and school lunches on an annual basis. This essay uses these values for the cash value of in-kind government transfers. The Census Bureau recognizes in-kind transfers as an important resource for low income households and has since included their market value in their Supplemental Poverty Measure (Interagency Technical Working Group, 2010).

This essay imputes the value of tax credits and tax liabilities using the NBER TaxSim 9.0. Tax credits include the EITC. Tax liabilities include federal and state tax liabilities as well as FICA and SECA taxes based on the tax laws in effect in each year (see Feenberg and Coutts (1993) for more information on the TaxSim program). The CPS samples households which can include multiple tax filing units, thus each household is divided into tax units prior to imputing tax credits and liabilities using the same procedure outlined in Burkhauser *et al.* (2012), which is based on the same assumptions on tax units first used by Piketty & Saez (2003).

The Census Bureau also imputes the full market value of employer and government provided health insurance based on the cost of provision. Employers' contributions are imputed at their full cash value. The Census Bureau first determines whether an individual is covered by an employer sponsored health insurance plan and whether the employer paid for all, part or none of the plan premium. Next, persons in the March CPS are statistically matched to persons in the National Medical Care Expenditure Survey or Medical Expenditure Panel Survey (depending on survey year) based on several demographic characteristics to impute the cash value of employer contributions. Census uses this imputed value as its measure of the value of private insurance for covered workers. Individual expenditures on employer sponsored health insurance plan premiums or expenditures on small-group/individual market health plans come from other income sources and are not included as income.

The Census Bureau also imputes the fungible and market values of government subsidized health insurance (Medicare and Medicaid). First, the Census Bureau determines the average government cost of providing Medicare and Medicaid by state and risk class. The two risk classes for Medicare are aged and disabled. The four risk classes for Medicaid are aged, disabled, children, and adults.[32] Thus, the imputed average cost of government provided health insurance varies by state and means of accessing government insurance.

The fungible values of Medicare and Medicaid are computed differently from the cash value of employer subsidies to health insurance. Rather than assume, as in the case of employer provided insurance, that this non-wage compensation is a perfect substitute for wages and hence on the margin can be valued at its cost to the employer, the fungible value does not make this assumption. Instead it assumes that persons whose income is not sufficient to purchase "basic food and housing requirements" as estimated by a poverty threshold are

[32] The Medicare and Medicaid risk classes reflect the channel through which benefits were accessed. The Medicare risk class "aged" applies to all persons on Medicare aged 65 or older. The Medicare risk class "disabled" applies to all persons accessing Medicare benefits through the SSDI program. The Medicaid risk class "children" applies to children accessing Medicaid benefits through either traditional Medicaid or a state's Children's Health Insurance Program (CHIP). The Medicaid risk class "adults" applies to all adults under the age of 65 accessing Medicaid benefits. The Medicaid risk class "aged" applies to all persons accessing Medicaid aged 65 or older. Lastly, the Medicaid risk class "disabled" applies to all persons accessing Medicaid benefits due to their qualification for SSI benefits.

deemed to put no value on government provided health insurance, and hence place a fungible value on it of zero.[33] For persons not in poverty, the fungible value of government insurance is estimated at its full market value, as is the case for employer sponsored health insurance.

Like Burkhauser, Larrimore, & Simon (2012) and Armour, Burkhauser, & Larrimore (2013), this essay uses the full market value of employer and government provided health insurance. For persons above the poverty line this is the Census imputed measure of the fungible value of government provided public insurance. For those at or below the poverty line, the Census Bureau's imputation formula is used, this value is not replaced with a zero.

The unit of analysis in this essay is the individual. To account for economies of scale in household consumption, household income is divided by the square root of the number of persons in the household. This size adjustment is common in US and international research studies of income trends and inequality (for example, see Gottschalk & Smeeding, 1997; Atkinson & Brandolini, 2001; Burkhauser *et al*., 2011, 2012; d'Ercole & Förster, 2012; Ruggles, 1990). All incomes are subsequently adjusted to 2010 dollar amounts using the Consumer Price Index Research Series (CPI-U-RS) (Steward & Reed, 1999).

3.4.5 Decomposition of Income Growth

This essay disentangles changes in income due to short-run business cycle fluctuations from long run economic trends by analyzing income growth over similar trough points in the business cycle—1983-1993, 1993-2004 and 2004-2011.[34] Using shift-share

---

[33] See Census Bureau technical documentation http://www2.census.gov/prod2/popscan/tp-58.pdf

[34] Official NBER macroeconomic business cycle recession years are denoted in gray vertical bars in all figures. In these analyses, peak and trough business cycle years are defined by peaks and troughs in median market income with one exception. Because median income only slightly increased in 1983 and unemployment rates persisted above 10 percent for half of that year, this essay considers 1983 rather than 1982 to be the last year of that recession.

methods, this essay decomposes income and isolates factors that contribute to income changes over business cycle trough years. These methods have been used by Burtless (1999), Iceland (2003), Daly & Valetta (2006), Larrimore, Burkhauser & Armour (2013), and Larrimore (forthcoming). Shift-share analysis does not demonstrate causality, but can account for changes in income over time due to fluctuations in demographic characteristics and source incomes. Using shift-share methods allows demographic composition and source incomes of the population to change one factor at a time, with the estimated contribution of each factor conditional on the previous factors.

The decomposition of income growth uses two methods. The first, from Atkinson (1998) and Burtless (1999), estimates income changes due to changes in the fraction of the population in subgroups. For example, this method considers how declining marriage rates affect the overall income distribution. This method compares one trough year to the next trough year (for example, 1983 and 1993), with observations from the base year (1983) reweighed so the fraction in each demographic group matches the fraction in the future trough year (1993). For example, the weights of individuals in 1983 increase for demographic groups which become more prevalent in 1993 and decrease for demographic groups that become less prevalent. This method accounts for changes in income between two trough years from changes in the fraction of demographic characteristics without altering the underlying income distributions within each demographic group.[35]

The second method, from Burtless (1999), Daly & Valetta (2006) and Larrimore (forthcoming), considers changes in source level income distributions and correlations across income sources within population subgroups. This technique allows the income distributions within demographic subgroups to change, and allows the changes in source level incomes to be correlated. An individual's income can be disaggregated into the sum of their source incomes. Let Y_{ik}^{t} be the total income in year t of individual i from demographic subgroup k. Equation 3.1 shows that total income is the sum of all person i's income sources f_{1ik}^{t} through (equation 3.1):

$$f_{Nik}^{t}.Y_{ik}^{t} = f_{1ik}^{t} + f_{2ik}^{t} + \cdots + f_{Nik}^{t}$$

To account for changes in the income distribution of the first factor f_{1ik}^{t}, the method assigns a percentile rank $p_{f_{1ik}}$to each individual for the first income source within each demographic group k. It then matches the percentile for each person within a demographic subgroup in the base year (for example, 1983) to the income calculated from the matching percentile from that demographic subgroup in the subsequent trough year (for example, 1993). Equation 3.2 then calculates a new income measure

[35] The demographic characteristics used were age brackets 18-44 and 45-64, race categories white and non-white, marital status of the householder (Marital status is the marital status of the household head, who can either be married, a single male, or a single female.), employment (yes or no), and receipt of SSI/DI benefits (yes or no).

by replacing the first source income in the base year with the matched first source income from the subsequent trough year (equation 3.2):

$$\widehat{Y_{ik}^{t'}(p_{f_{1ik}})} = f_{1ik}^{t'}(p_{f_{1ik}}) + f_{2ik}^{t} + \cdots + f_{Nik}^{t}$$

The new income measure $\widehat{Y_{ik}^{t'}(p_{f_{1ik}})}$ is an estimate of person i from demographic subgroup k's income in the subsequent trough year conditional on changes in only demographic characteristics and income from the first source.

The next step uses Equations 3.3 and 3.4 to account for correlations between income sources by iteratively combining and assigning income sources a percentile based on the combined income source. For example in Equation 3.3 a new income source is defined which is equal to the sum of income source 1 and 2 (equation 3.3):

$$g_{1+2ik}^{t} = f_{1ik}^{t} + f_{2ik}^{t}$$

A percentile rank q_{1+2ik} is then assigned to each individual for the sum of income sources 1 and 2 within each demographic subgroup k. The percentile for each person within a demographic subgroup in the base year (for example, 1983) is matched to the income calculated from the matching percentile from that demographic subgroup in the subsequent trough year (for example, 1993). A new income measure is then calculated by replacing the sum of income sources 1 and 2 in the base year with the matched sum of source 1 and 2 income from the subsequent trough year (equation 3.4):

$$\widehat{Y_{ik}^{t'}(q_{g_{1+2ik}})} = g_{1+2ik}^{t'}(q_{g_{1+2ik}}) + f_{3ik}^{t} + \cdots + f_{Nik}^{t}$$

The new income measure $Y_{ik}^{t'}(\widehat{q_{g_{1+2ik}}})$ is an estimate of person i from demographic subgroup k's income in the subsequent trough year conditional on changes in only demographic characteristics, the level of source 1 and 2 incomes, and the correlation between source 1 and 2 incomes. This process is iterated with additional incomes absorbed by g until all source incomes have been considered. For example, the g defined for income source 3 is $g_{1+2+3ik}^{t} = f_{1ik}^{t} + f_{2ik}^{t} + f_{3ik}^{t}$.

After each step in the shift-share analysis, the shift-share algorithm calculates a theoretical income statistic based on only the considered factors changing. For example, in step one, changes to income based on shifts in the age distribution are considered. This step generates a theoretical income measure for the subsequent trough year that would prevail if only the age distribution changed. The algorithm compares this measure to the actual observed income measure in the base year. The difference between the two measures is presumably due to changes in the age distribution. The next factor considered is race, this step estimates the impact from a change in the race structure between the two years conditional on the change in the age distribution. The interpretation for changes in source incomes is very similar as well. For example, the median of $Y_{ik}^{t'}(\widehat{q_{g_{1+2ik}}})$ for all i and k is generated. The algorithm compares this statistic to the median of Y_{ik}^{t} for all i and k. The difference between the two is presumably due to changes in all specified demographic characteristics and changes in the level and correlation of sources 1 and 2. Ultimately, these shift share techniques compare all of these differences to the true income statistic in the subsequent trough year to determine the percentage point contribution of each factor to changes in the income measure.

3.5 Results

3.5.1 Summary Statistics

Table 3.1A and Table 3.1B respectively report demographic characteristics for those with and without a work limitation, our disability measure for each trough year of the analysis – 1983, 1993, 2004 and 2011. Persons with disabilities are on average older, less likely to be employed, less likely to be married, and far more likely to be receiving disability benefits through either SSDI or SSI.

Table 3.1: Demographic Characteristics of People with and without Disabilities

Year	N	Weighted N	Age	Male	White	Full Time	Part Time	Householder	Married	Receive SSI/DI
Panel A - Without Disabilities										
1983	90,571.00	132,735,786	36.75	0.49	0.83	0.48	0.33	0.78	0.73	0.01
1993	83,035.00	146,354,650	37.67	0.49	0.79	0.55	0.3	0.77	0.68	0.01
2004	116,471.00	167,580,422	39.37	0.49	0.74	0.59	0.25	0.77	0.64	0.01
2011	112,809.00	177,367,748	39.96	0.49	0.71	0.54	0.25	0.73	0.61	0.02
Panel B - With Disabilities										
1983	6,999	10,365,064	46.92	0.51	0.79	0.13	0.22	0.8	0.61	0.27
1993	6,952	12,753,461	45.41	0.52	0.73	0.11	0.24	0.76	0.53	0.35
2004	9,461	14,536,005	46.85	0.49	0.71	0.09	0.18	0.75	0.46	0.44
2011	9,449	15,777,357	48.37	0.49	0.7	0.06	0.16	0.75	0.44	0.48

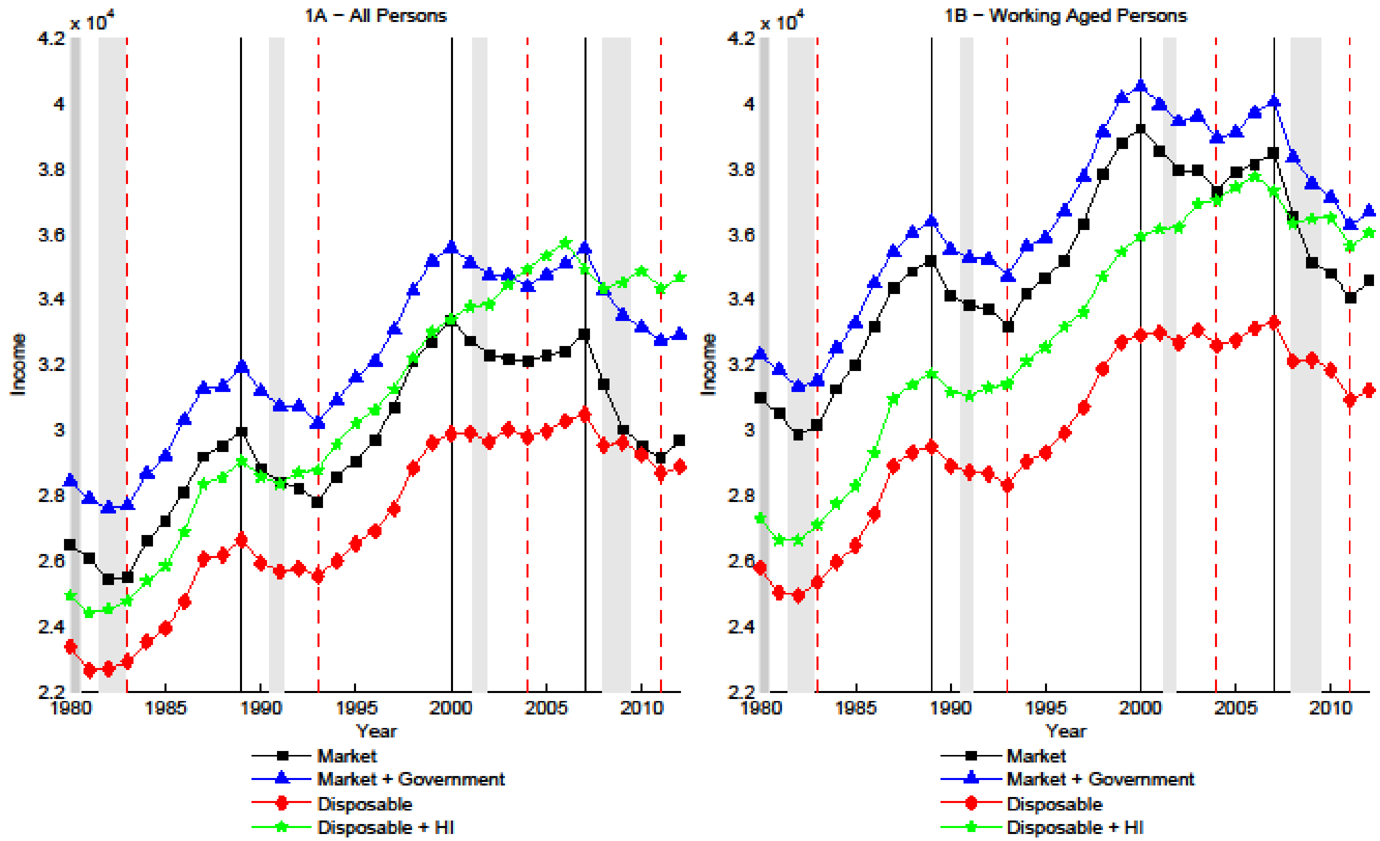
Source: Author’s estimation from March CPS data.

3.5.2 Trends in Median Income

Figure 3.1A replicates, from 1980 to 2012, levels and trends in the size-adjusted household income of the median person in the United States using CPS data based on each of the four measures of income found in Armour, Burkhauser & Larrimore (2013, forthcoming). Official NBER recession periods are shaded. As discussed above, rather than use these years to compare business cycle troughs years, Figure 3.1 and all subsequent figures and tables define a trough year as the last year in which median market income falls following a recession – 1983, 1993, 2004 and 2011 – and peak years are defined as the highest median market income year between these troughs – 1989, 2000, and 2007. With the exception of 1983, the median market income trough years follow the official NBER recession ending years. This is the case, because the major component of market income is labor earnings and it is a lag indicator of business recovery.

The level of median income varies across its four definitions. As the sources of income increase, so does median income. Median market income (income definition 1) is below market and government income (income definition 2) in all years. But the difference has grown over time as the value of government transfers received by the average American increased. Disposable income is a fuller measure of available resources and for the median American, its value lies below market income in all years. That is, when government taxes as well as government transfers are considered, median disposable income is below market income for the average American. However, this difference was much smaller during the Great Recessions years (2007-2011) than during previous recessions—a major finding of Armour, Burkhauser and Larrimore (2014) using this measure of income.

Most relevant for this essay however is that adding the insurance value of employer and government provided health insurance to disposable income for people with and without disabilities, not only increases median income in all years, but does so to such a degree that after trough year 1993, median income increases every year until 2006, the year before the start of the Great Recession. This period includes the years 2000-2004 over which median market income declined and 2001-2002, an NBER recession year. While median disposable income and disposable income including health insurance measures fell from 2006-2008, they stabilized thereafter at higher values relative to their peak years than the first two income definitions.



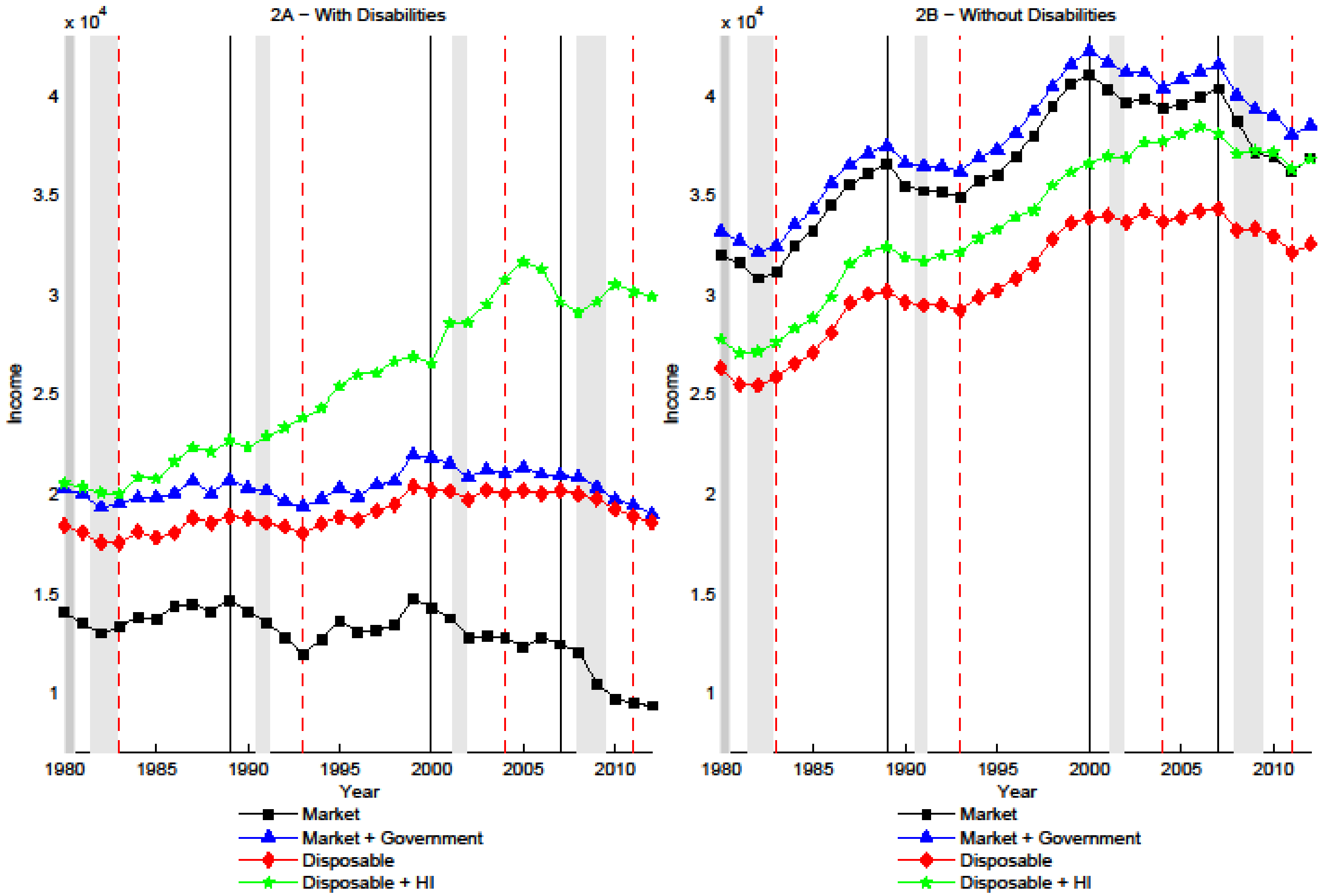
Source: Author's estimation from March CPS data.

Figure 3.1: Trend in Median Size-Adjusted Household Income of Persons

3.5.3 Comparing Levels and Trends in the Incomes of Working Age People with and without Disabilities

Figure 3.1B focuses on median income levels and trends for the working age (18-64) population. The trough years are unchanged. But because this is a working age population (older and younger persons are included only to the extent that they live in the households of working age persons and contribute to household income), the market income of the median person is considerably higher than was the case in Figure 3.1A. The levels of the other three measures of median income are also higher relative to their Figure 3.1A counterparts but to a lesser degree. As a result, the median household size adjusted income of the median person as measured by disposable income plus health insurance never exceeds the more traditional market and government income median values. But the difference between them lessens each year from 1993 through 2006.

Figure 3.2 disaggregates the working age population into those with disabilities (Figure 3.2A) and those without disabilities (Figure 3.2B). The market income of the median working age person with disabilities is somewhat sensitive to general economic conditions over the first two full business cycles captured trough to trough in the data (1983-1993-2004) but less so in the third (2004-2011). It rises slightly from its 1983 trough through peak year 1989 before plunging to an even lower trough in 1993. It then rises to a 1999 peak year high before returning to approximately its 1993 level during trough year 2004. It continues to fall in 2005 but does rise slightly in 2006. It has fallen continuously since then to a record low during trough year 2011, well below its previous 2004 trough value. It fell again in 2012. Over the three full business cycles Figure 3.2A captures, median market income fell from $13,304 in 1983 to $9,448 in 2011 with most of the decline occurring in the first and third business cycle.



Source: Author's estimation from March CPS data.

Figure 3.2: Trend in Median Size-Adjusted Household Income of Persons with and without Disabilities

This substantial drop in market income has been offset by increases in other sources of income. Median market and government income is not only higher in all years, but the growth of government transfers has increasingly mitigated the drop in market income over time. Median disposable income is slightly lower than market and government income in all years but this difference is smaller in later years. The disposable income of the median working age person with a disability rose slightly over each of the first business cycles and fell modestly over the third. Over the three full business cycles Figure 3.2A captures, median disposable income rose from $17,529 in 1983 to $18,009 in 1993, and again increased to $19,989 in 2004. Disposable income then fell from its 2004 level to $18,840 in 2011.

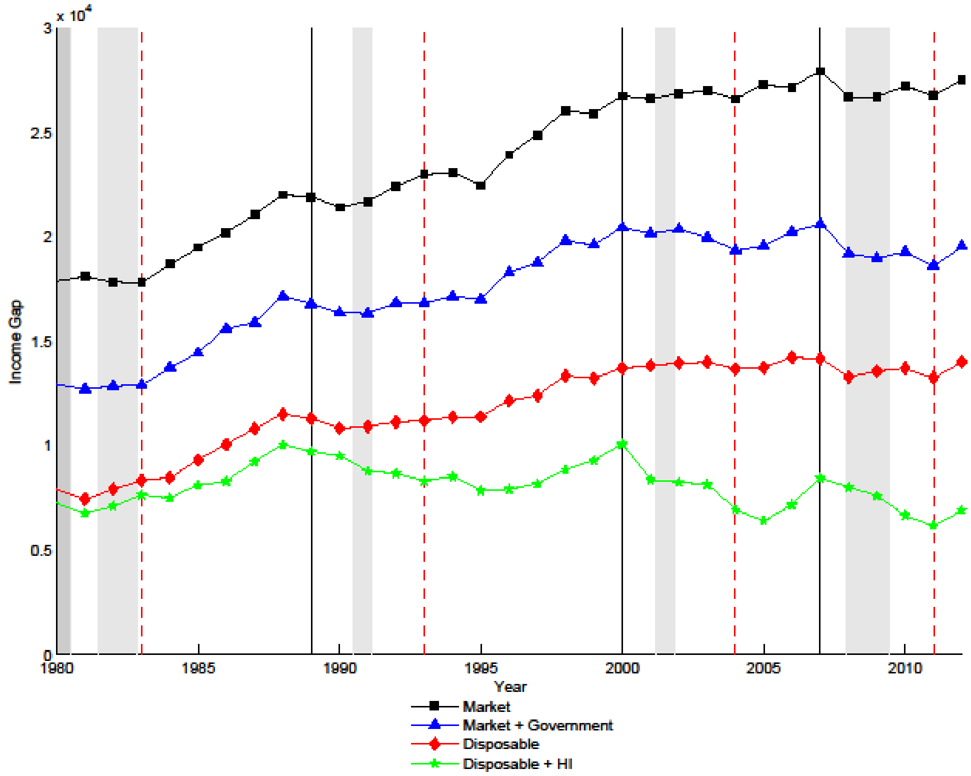
Including the insurance value of employer and government provided health insurance dramatically changes median income levels and trends for this population. In 1983 there is very little difference between measured median disposable incomes including or excluding health insurance. But the substantial increase in the value of employer and government provided health insurance for this population profoundly affects median disposable income. Median income rises substantially over the first two business cycles, peaks in 2005 before falling to a low in 2008. The growth in the value of health insurance thereafter more than offsets the decline in other income so that median income rose from 2008-2010 and then fell reflecting the trend in the other three median income measures. Over the entire three business cycle period (1983-2011) however median disposable income plus health insurance increased from $19,978 to $30,137.

Figure 3.2B is very similar in levels and trends to Figure 3.1B. This is not surprising since working age people without disabilities made up between 91.8% and 93.1% of the total working age population over this period. The market income of this population is much more sensitive to business cycles peaks and troughs than is median income for working aged people with disabilities. However, in contrast to Figure 3.1A, the market income of the median working age person without disabilities grew substantially over the first two business cycles (from $31,117 in 1983 to $34,862 in 1993 to $39,336 in 2004). But, like working age people with disabilities, it fell over the last business cycle and was $36,213 in 2011. But, unlike Figure 1A, it increased in 2012 to $36,888.

3.5.4 The Income Gap Between Working Age People with and without Disabilities

Figure 3.3 focuses on levels and trends in the gap in median income of working age people with and without disabilities from 1980-2012. The figure simply subtracts the median income values by year for each income definition in Figure 3.2A from their counterparts in Figure 3.2B. The gap is largest for market income. It grew substantially over the first two business cycles, but especially during period of economic growth between 1983-1989 and 1995-2000. The gap remained the same over the most recent 2004-2011 business cycle. Over all three business cycles however the gap has grown from $17,813 in 1983 to $26,764 in 2011. The gap is somewhat smaller for market and government income, but the trends are the same. Over the three business cycle the gap has grown from $12,908 in 1983 to $18,633 in 2011. The gap is even smaller for disposable income, but the trends are the same. Over the three business cycles, the gap has grown from $8,346 in 1983 to $13,260 in 2011.

Not only is the gap smaller once the value of health insurance is added to disposable income, but the trends are different. While the gap increases during growth periods, similar to the other three median income measures, the decline after the peak year is smaller so that the overall gap remained the same for the business cycle of 1983-1993, and actually fell between 1993 and 2004. There is almost no change between 2004 and 2011 for the same reasons. Over the three business cycles, the gap has declined from $7,636 in 1983 to $6,164 in 2011.



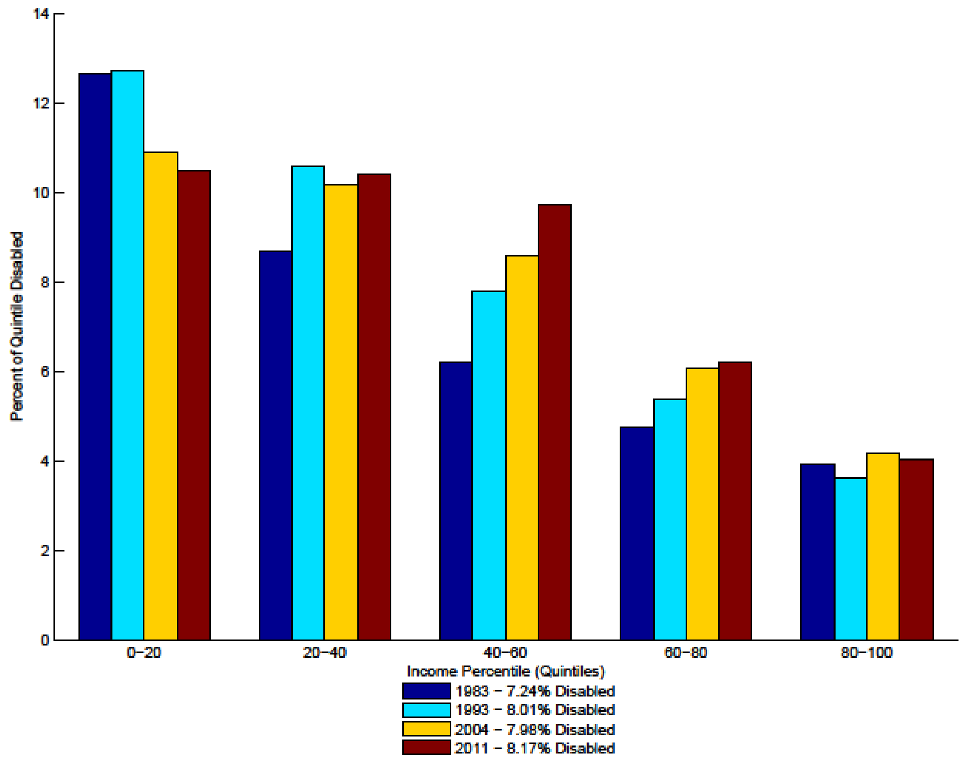
Source: Author's estimation from March CPS data.

Figure 3.3: Trend in the Median Size-Adjusted Household Income Gap Between Persons with and without Disabilities

3.5.5 Change in the Characteristics of those in the Lowest Income Quintile of the Population

Figure 3.3 shows that once the value of health insurance is included in a fuller measure of disposable income, the gap in median income between working age people with and without disabilities falls from 1983-2011. Figure 3.4 uses this same fuller measure of disposable income to show that the share of the working age population in the lowest quintile also falls. In 1983 working age people with disabilities made up 12.66 percent of the working age population in the bottom income quintile of the population. Despite the fact that the prevalence of disability in the working age population rose slightly from 7.24 percent to 8.17 percent, the share of people with disabilities in the bottom income quintile fell to 10.49

percent in 2011. Over the same period, the percentage of people with disabilities in the middle three quintiles rose with little change in the top quintile.



Notes: The percent disabled reported in the legend represents the composition of the overall working aged population that is comprised of people with disabilities in the stated year.
Source: Author's estimation from March CPS data.

Figure 3.4: Fraction of Trough Year Full-Income Quintiles Consisting of Persons with Disabilities

3.5.6 Changing Portfolio of Income Sources for Persons with and without Disabilities

Figure 3.3 shows that using a fuller measure of disposable income that includes the value of employer and government provided health insurance not only reduces the gap in the median income of working age people with disabilities, but also shows that the gap has been narrowing over the last three business cycles. Figure 3.4 shows, using this fuller measure of income, that the share of working age people with disabilities in the bottom quintile of the population has also fell over the last three business cycles. Table 3.2 provides some insight into the growing importance of health insurance in the income portfolio of working age people with disabilities. It does so by showing how the share of mean income, by income source, for working age people with and without disabilities across nine non-overlapping sources changed across the four trough years discussed above. This table takes advantage of the fact that mean income in any year can be divided into the sum of the mean of its sources when there are no negative sources of income.

To do this, this essay focuses on estimated gross income in a household from private and government sources including the value of health insurance and divides it into its nine components. The first three (own labor earnings, the labor earnings of others in the household and private non-labor income) represent total in cash market income (income definition 1). The next two (SSDI/SSI cash transfers and all other government transfers) represent total in cash government transfers. These first five sources of income make up income definition 2. The next is government in-kind transfers excluding health insurance. The first six sources of income represent the total gross income before taxes used in disposable income (income definition 3). For the moment this essay does not consider the effect of taxes on this gross income measure. The last three (the value of employer provided health insurance, the value of government provided health insurance to those receiving SSDI/SSI, and the value of all other government provided health insurance) represent the value of employer and government provided health insurance used in income definition 4.

Table 3.2: Trends in Share of Gross Mean Income Including the Value of Health by Income Source for Persons with and without Disabilities

year	Mean Gross Income	Own Labor Income	Others Labor Income	Private Non-Labor Income	SSI/DI Cash Transfers	SSI/DI Health Insurance	Other Public Health Insurance	Public Non-Labor Cash Transfers	Public Non-Cash Transfers	Private Health Insurance	Total Share	Taxes
						With Disabilities						
1983	27,487.26	17.45	37.52	15.83	13.21	4.89	1.29	6.07	1.10	2.64	100.00	15.46
1993	31,103.74	15.43	34.54	12.46	14.67	10.72	2.51	5.21	1.29	3.16	100.00	11.92
2004	38,587.80	11.75	32.66	11.61	15.43	17.18	3.72	3.62	0.81	3.21	100.00	10.13
2011	37,100.72	8.23	32.20	10.87	18.00	18.43	4.32	3.70	1.47	2.78	100.00	8.99
						Without Disabilities						
1983	39,212.75	40.12	43.80	7.52	1.98	0.49	0.38	1.73	0.34	3.65	100.00	23.65
1993	47,613.47	40.76	42.16	7.54	1.80	0.83	0.60	1.30	0.32	4.68	100.00	22.25
2004	55,181.30	41.62	41.35	6.85	1.75	1.28	0.85	0.69	0.20	5.41	100.00	20.34
2011	53,477.97	40.49	41.46	6.29	2.19	1.58	1.37	1.19	0.39	5.05	100.00	19.36

Source: Author's estimation from March CPS data.

When these nine values are summed they represent 100 percent of the gross income of the working age population which is disaggregated between working age people with and without disabilities in Table 3.2. The yearly mean of this gross income value is reported in column 1 of Table 3.2. The next nine columns report the share of each of these sources of gross income before taxes that are used in income definitions 3 and 4. The final column reports the share of gross income that was paid in taxes. But this essay separates this negative value from the four positive values that sum to 100 percent of gross income.

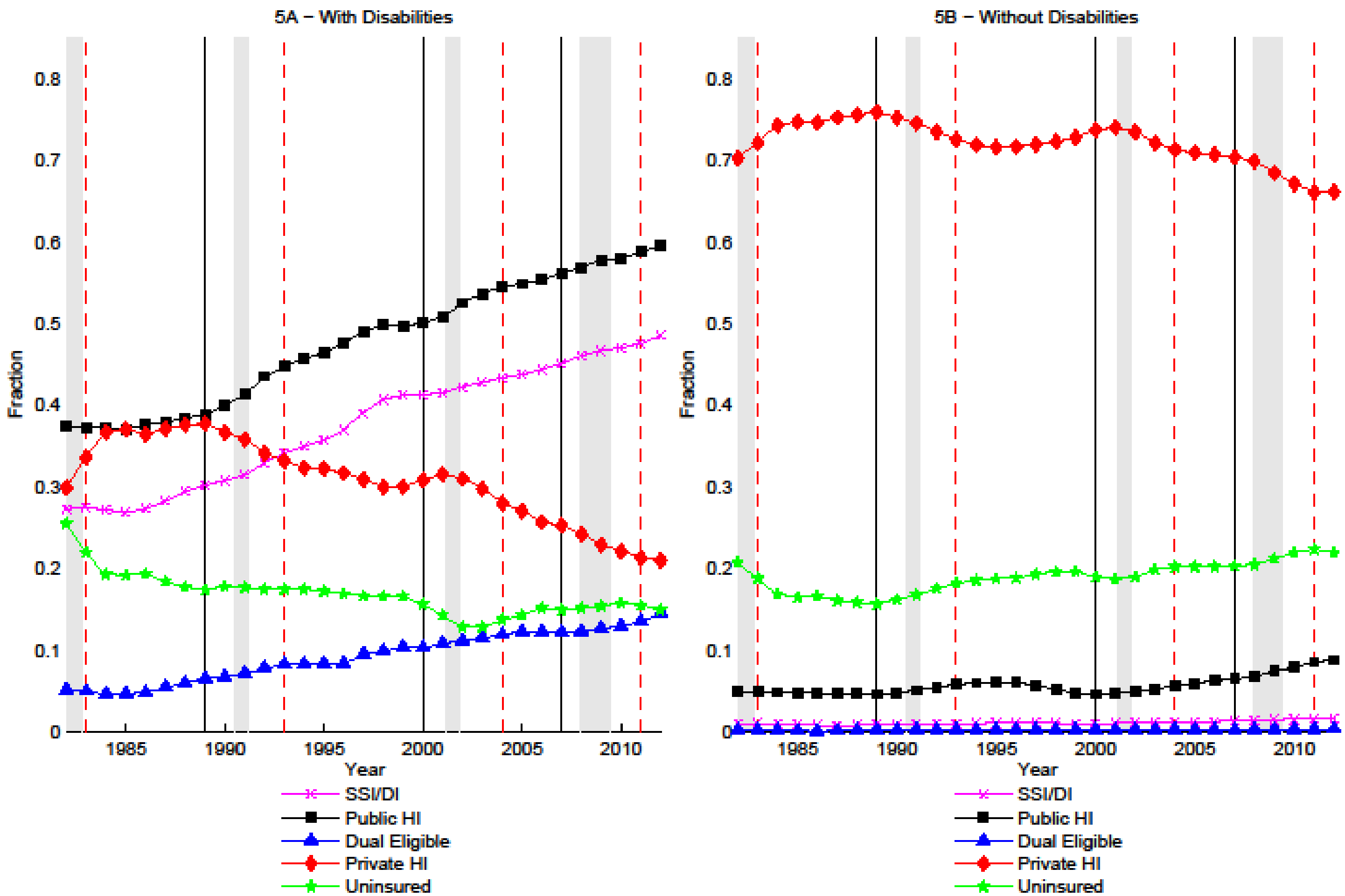
For those without disabilities, market income provides the overwhelming share of gross income: 91.44 percent in 1983. While this falls slightly across the other three trough years 90.46 percent in 1993, 89.82 percent in 2004 and 88.24 percent in 2011, market income is by far the dominant source of income for working age people without disabilities. Government in-cash transfers in these four trough years are 3.71, 3.10, 2.44, and 3.38 percent respectively. Government non-cash transfers are 0.34, 0.32, 0.20 and 0.39 respectively—small components of gross income that have varying importance over the four trough years. While private and government health insurance values are also small relative to market income they are more important than these government sources of gross income at 4.52, 5.60, 6.95 and 8.00 percent and they have been growing over time. As can be seen directly in Table 3.2, the primary source of this growth was employer provided insurance over the first three trough years but this value fell as a share of gross income by 2011. A far more important government factor with respect to gains in disposable income of this population is the share of gross income that is taxed. It fell from 23.65 percent in 1983 to 22.25 in 1993 to 20.34 in 2004 and 19.36 in 2011.

The relative importance of these nine sources of gross income and their trends over this same period much more remarkable for working aged people with disabilities. Market income made up 70.80 percent of gross income in 1983. This fell to 62.43, 56.02 and 51.30 over the next three trough years. Somewhat surprisingly while SSDI/SSI cash transfers increase to some degree over the period from 13.21 percent in 1983 to 15.43 percent in 2004 this is almost entirely offset by declines in other government cash transfers so that total government in-cash transfers only fell slightly from 19.28 to 19.05. However in 2012 SSDI/SSI jumps to 18.0 percent, and total government in cash transfers increase to 21.70 percent. Government non-cash transfers are 1.10, 1.29, 0.81 and 1.47 respectively—small components of gross income that have varying importance over the four trough years. But it is private and government health insurance whose share of gross income increased the most from 8.82 percent in 2003 to 16.39 percent in 1993 to 24.11 percent in 2004 to 25.53 percent in 2011. As can be seen directly in Table 3.2 the rise in the share of income coming from government provided Medicare and Medicaid to SSDI/SSI recipients is driving this increase in share from 4.89 percent in 1983 to 10.72 percent in 1993 to 17.18 percent in 2004 to 18.43 percent in 2011.

To give some perspective on this rise in the share of income, in 1983 health insurance was the fifth most important source of income for working age people with disabilities behind the market income from others earnings, own earnings, and private non-labor earnings and SSDI/SSI cash transfers respectively. It remained in fifth place in 1993 but rose to second place behind only the labor earnings of others in the household by 2004 and at 18.43 percent remains in second place. Taxes are a much smaller component of disposable income for working age people with disabilities but they also have fallen over time from 15.46 percent in 1983 to 8.99 percent in 2011.

Figure 3.5 provides additional insights into why the share of health insurance in these two working age populations has varied over the last three business cycles. Figure 3.5A reports levels and trends in the share of those with disabilities who are receiving their health insurance as part of their SSDI/SSI benefit package. This has steadily grown from 27.5 percent in 1983 to 47.5 percent in 2011. When those who are receiving other government provided health insurance are included the numbers increase to 37.2 and 58.8 percent, respectively. Note however, almost all of the increase is from those receiving insurance as part of their SSDI/SSI package of benefits. Dual entitlement to both Medicare and Medicaid has risen from 5 percent in 1983 to 13.5 percent in 2011.[36]

[36] Dual entitlement or dual eligibility refers to persons who receive both Medicare and Medicaid benefits. Persons with disabilities can qualify for both insurance benefits if they qualify for both SSI and SSDI. This requires the person to have worked in a SSA qualified job and to be below specific asset limits (SSI is a means tested program).

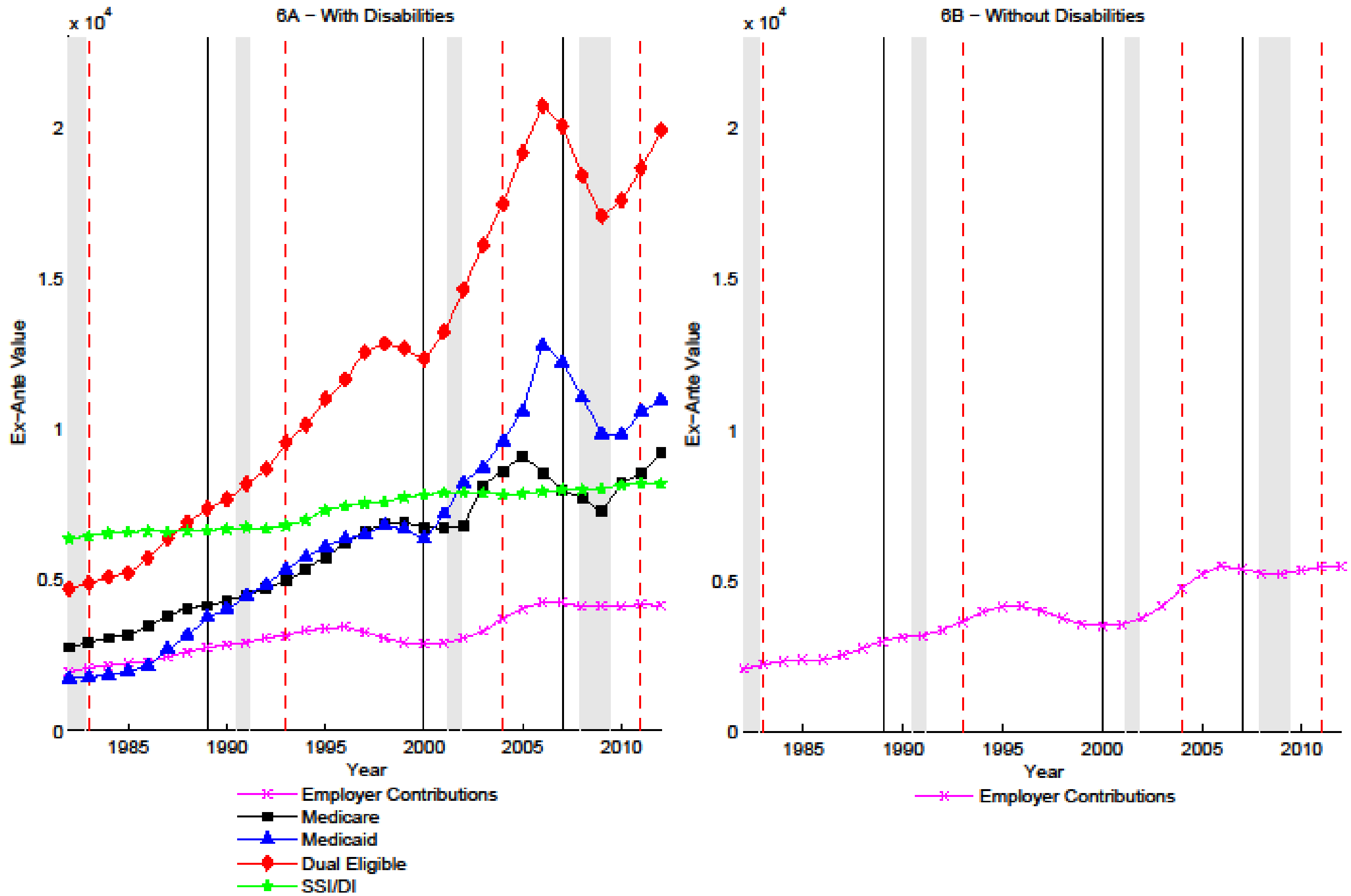


Source: Author's estimation from March CPS data.

Figure 3.5: Trend in Health Insurance and SSI/DI Take-Up for Persons with and without Disabilities

Over this same period employer provided health insurance fell from 33.5 percent in 1983 to 21.3 percent in 2011. On net the uninsured population fell from 21 percent in 1983 to 15.4 percent in 2011. Figure 3.5B shows that for working age people without disabilities, employer provide insurance has been the dominant source of health insurance. But after rising to an all-time high of 75.8 percent in the peak year—1989 of the 1983-1993 business cycle it as trended downward. It fell from 72.1 percent in 1983 to 66 percent in 2011. While a small but growing percentage of working age people without disabilities have gained access to health insurance via government programs, the uninsurance rate among working age people without disabilities has grown relative to those with disabilities.

While Figure 3.5 focuses on the types of health insurance held by working age people with and without disabilities, Figure 3.6 shows how the value of these types of health insurance have changed for the median person holding them. Figure 3.6A shows that for working age people with disabilities the value of all sources of employer and government provided health insurance held by the median person increased over all three business cycles, but especially over the 1993-2004 business cycle while growth in the value of employer provided and SSI/DI cash benefits were far less pronounced. This is consistent with the trends in share of these sources of income discussed in Table 3.3. Figure 3.6B focuses on working age people without disabilities and displays the growth in the value of their employer provide health insurance premiums. The median values of other sources of health insurance have been omitted for persons without disabilities because such a small fraction of this population relies on publicly provided health benefits (about 5 percent on average).



Source: Author's estimation from March CPS data.

Figure 3.6: Trends in the Market Value of Health Insurance and SSI/DI Benefits

3.5.7 Income Growth Decomposition via Shift Share Analysis

Up to now, this essay has described how the income measure used affects income disparities between people with and without disabilities. Recent literature has come to a consensus that disposable income (income definition 3) is preferred over market income or market plus government income (income definitions 1 and 2), when analyzing the flow of resources to a household. There is some debate over whether disposable income plus health insurance (income definition 4) is preferable to disposable income. As discussed above, using disposable income plus health insurance has recently been the preferred measure of income by the Congressional Budget Office (2012, 2013) and several academic researchers (Burkhauser, Larrimore, & Simon, 2012; Armour, Burkhauser, & Larrimore, 2013, forthcoming; and Aaron & Burtless, 2014). This essay has presented evidence from analyses and past literature to support the use of disposable income plus health insurance as the preferred measure of economic wellbeing. The change from disposable income to disposable income plus health insurance results in a dramatic change in income inequality results. Using the first three definitions of income, disparities between people with and without disabilities were found to have grown over the last three business cycles. Using disposable income plus health insurance reverses this finding.

This section uses the results from the previous sections of this essay to determine the factors most responsible for the closing of the income gap between people with and without disabilities. It does so by presenting the results from the decomposition of disposable income plus health insurance income growth over trough years in the three business cycles discussed above. Figure 3.2A presented levels and trends for disposable income plus health insurance over the last three business cycles for working age people with disabilities. Figure 3.2B did the same for working age people without disabilities. Using shift share analysis, this section will estimate the contribution of changing demographic characteristics and income sources to overall median disposable income plus health insurance growth between business cycle trough years.

Table 3.3 reports the factor growth decomposition between each trough year in the last three business cycles (1983-1993, 1993-2004, and 2004-2011) as well as the overall contribution of each factor from 1983 to 2011 for people with and without disabilities. The first row reports the percentage point change in median disposable income plus health insurance values for the respectively labeled business cycles.

Over the two business cycles where economic growth was positive, the growth in median disposable income plus health insurance was greater for those people with disabilities than for those without disabilities. From 1983 to 1993 the income of the median American with a disability grew by 19.27 percentage points (1.75 percentage points annually) relative to a growth of 16.34 percentage points (1.49 percentage points annually) for those without a disability. The difference in growth rates between the two populations was more pronounced over the 1993 to 2004 business cycle with median incomes increasing for those with disabilities by 29.06 percentage points (2.42 percentage points annually) compared to 17.31 percentage points (1.44 percentage points annually) for those without a disability. Over the last business cycle (2004-2011), while both populations experienced real income declines, the decline in income was less pronounced for working aged people with disabilities that for those without disabilities. Overall, from 1983 to 2011 median incomes of people with disabilities increased by 50.85 percentage points (1.75 percentage points annually) compared to an increase of 31.46 (1.15 percentage points annually) percentage points for working aged people without disabilities. Hence, over the last 28 years and three business cycles, the median income of working aged people with disabilities increased in relation to the median income of working aged people without disabilities, with the vast majority of the closing of the income gap between people with and without disabilities occurring over the 1993 to 2004 period. The rest of Table 3.2 decomposes income growth into its factor components to identify the source of income changes and subsequently the factor(s) most responsible for closing the income gap between those with and without disabilities.

The next 15 rows of Table 3.3 (rows 2-16) report the individual percentage point changes in median disposable income plus health insurance values accounted for by changes in demographics and source incomes for each of the three business cycles listed above and for the overall analysis period from 1983 to 2011. The sum of the 15 values in each column equals the total percentage point change displayed in the first row.

Table 3.3: Factor Decomposition of Median Disposable Income Plus Health Insurance Growth for Persons with and without Disabilities

	Median Incomes							
	1983-1993		1993-2004		2004-2011		1983-2011	
	Without Disabilities	With Disabilities	Without Disabilities	With Disabilities	Without Disabilities	With Disabilities	Without Disabilities	With Disabilities
1. Actual	16.34	19.27	17.31	29.06	-3.68	-2.00	31.46	50.85
2. Age	0.19	-0.36	1.73	0.45	0.71	0.39	2.29	0.32
3. Race	-1.48	-2.01	-1.85	-0.51	-1.24	-0.45	-4.41	-3.74
4. Marriage	-0.68	-2.31	-0.73	-2.11	-0.69	-0.54	-1.88	-6.68
5. Own Employment	2.34	-0.77	0.76	-1.05	-1.66	-0.80	1.29	-3.65
6. Own Labor Income	3.15	1.03	5.33	0.96	-0.46	0.09	7.50	1.99
7. N Other Workers	1.55	0.48	-0.75	-0.50	-0.39	-0.39	0.69	0.02
8. Other's Labor Income	6.38	0.23	9.19	7.49	-0.89	-1.38	14.80	8.87
9. Private Non-Labor Income	1.39	-0.17	0.21	0.34	-1.27	-1.11	0.10	-1.35
10. Receive SSI/DI	-0.11	3.24	-0.04	2.41	0.11	0.08	-0.13	5.38
11. SSI/DI Cash	0.14	0.72	0.44	1.62	-0.43	-1.13	0.89	3.64
12. SSI/DI HI	0.79	14.08	0.87	17.21	0.57	0.85	2.61	35.23
13. Other Public HI	0.10	1.85	0.72	3.07	0.38	0.58	1.58	7.24
14. Other Public Transfers	-0.11	0.88	-0.54	-1.25	0.72	1.05	0.37	0.96
15. Taxes	-0.29	1.28	0.00	-0.42	1.39	0.96	1.25	0.51
16. Private HI	3.01	1.10	1.94	1.36	-0.52	-0.03	4.51	2.10

Source: Author's estimation from March CPS data.

This essay first considers three important demographic trends: an aging population, a more racially diverse population, and declining marriage rates. Tables 3.1A and 3.1B display these demographic trends for both those with and without disabilities. Both working aged populations grew older. The average age of a person with a disability increased from 46.92 years in 1983 to 48.37 years in 2011. The population of people without a disability similarly aged, increasing the average age from 36.75 in 1983 to 39.96 in 2011. Furthermore, both populations experienced an increase in the distribution of non-whites over the last 30 years. The distribution of white people with disabilities fell from 79 percent in 1983 to 70 percent in 2011, a decrease of 9 percentage points. The corresponding decrease in the white population for people without disabilities was from 83 percent in 1983 to 71 percent in 2011, a decrease of 12 percentage points. Lastly, marriage rates fell for both populations as well. The percent of people with disabilities living in a household in which the head of the household is married fell from 61 percent in 1983 to 44 percent in 2011, a decrease of 17 percentage points. The population people without disabilities experienced a very similar percentage point decline from 73 percent married in 1983 to 61 percent in 2011.

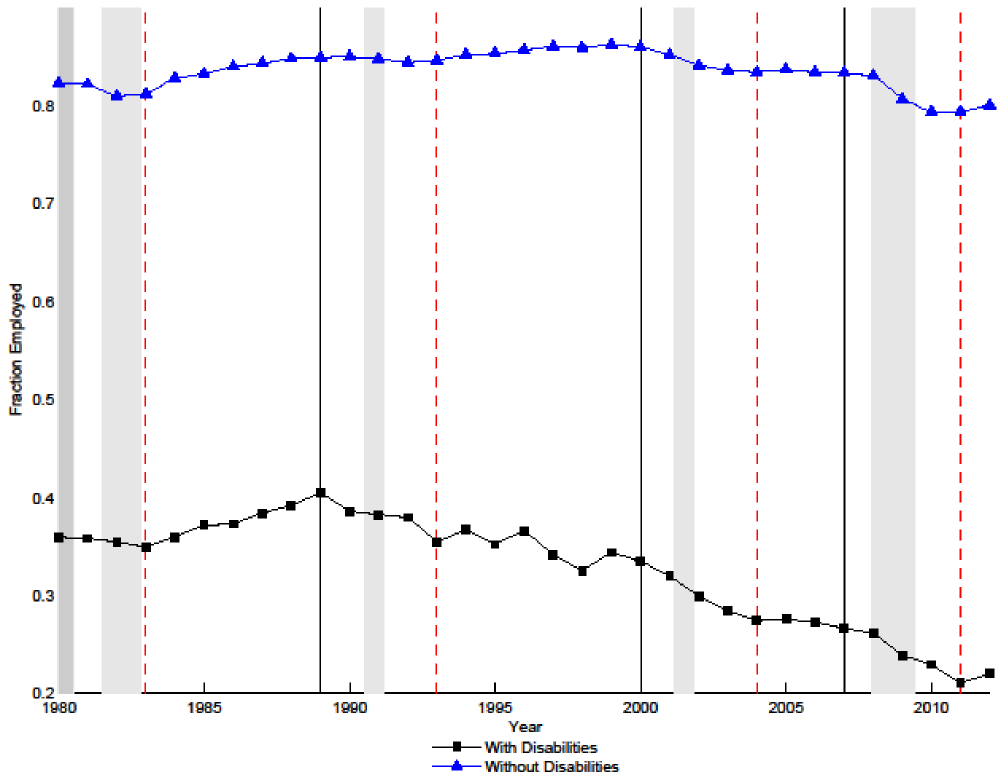
Table 3.3 (rows 2 through 4) report the changes accounted for by these demographic trends over each of the three business cycles, as well as for the entire analysis period from 1983 to 2011. The income changes attributed these demographic trends hold the underlying income distributions within each demographic subgroup constant at the base year income level. Thus, these estimates capture only changes in the distribution of demographic subgroups from one trough year to the next, and not changes in the income distribution.

The contribution of the ageing population to income changes across each business cycle varies for both those with and without disabilities. From 1983 to 1993 age accounted for 1 percent (0.19 percentage points) of the increase in median incomes for people without disabilities, while ageing of the population of people with disabilities decreased median incomes by 0.36 percentage points. From 1993 to 2004 aging contributed to an increase in median incomes of 1.4 percent (0.45 percentage points) and 8.7 percent (1.73 percentage points) for those with and without disabilities, respectively. From 2004 to 2011, despite a real decline in median incomes for both populations of people with and without disabilities, the aging of both populations accounted for a positive contribution to median income growth of 0.39 and 0.71 percentage points, respectively. Over the entire analysis period from 1983 to 2011, aging accounted for 0.5 percent (0.32 percentage points) and 6.1 percent (2.29 percentage points) of the increase in median incomes for people with and without disabilities, respectively. Thus, over each business cycle, aging contributed to higher growth rates in median incomes for people without disabilities; however the magnitude of the contribution to median income changes for both populations was small relative to the overall change.

The increasing racial diversity of Americans over the last three decades reduced growth in median incomes for both those with and without disabilities. From 1983 to 1993, this factor accounted for 2.01 (41 percent of negative growth) and 1.48 (60 percent of negative growth) percentage points of reduced growth for people with and without disabilities, respectively. Similarly, the numbers for 1993 to 2004 were 0.51 (16 percent of negative growth) and 1.85 (71 percent of negative growth), and from 2004 to 2011 were 0.45 (9 percent of negative growth) and 1.24 (17 percent of negative growth). Over the entire analysis period, increasing racial diversity accounted for 3.74 and 4.41 percentage points of negative growth for those with and without disabilities, respectively. These, changes accounted for 28 percent of reduced median income growth for those with disabilities and 70 percent of reduced median income growth for those without disabilities. Therefore, the increase in the distribution of non-whites (relative to whites) over the past 30 years has contributed to reduced median income growth rates for both those with and without disabilities. However, the impact of increased racial diversity has a much stronger negative growth rate effect on people without disabilities, accounting for a majority of reduced median income growth in all business cycles (except 2004 to 2011 in which real income declined).

Declining marriage rates served to slow income growth over the last three decades as well. From 1983 to 1993, this factor accounted for 2.31 (48 percent of negative growth) and 0.68 (28 percent of negative growth) percentage points of reduced growth for people with and without disabilities, respectively. Similarly, the numbers for 1993 to 2004 were 2.11 percent (67 percent of negative growth) and 0.73 percent (28 percent of negative growth), and from 2004 to 2011 were 0.54 percent (11 percent of negative growth) and 0.69 percent (10 percent of negative growth). Over the entire analysis period, increasing racial diversity accounted for 6.68 and 1.88 percentage points of negative growth for those with and without disabilities, respectively. These, changes accounted for 50 percent of reduced median income growth for those with disabilities and 30 percent of reduced median income growth for those without a disability. Therefore, the decline in marriage rates over the past 30 years has contributed to reduced median income growth rates for both those with and without disabilities. However, the impact of this decline had a much stronger negative growth rate effect on people with disabilities, accounting for almost half of reduced median income growth in all business cycles (except 2004 to 2011 in which real income declined).

Next, this essay considers changes in employment and labor income. The employment and labor earnings of the individual are considered along with the number of other employed persons and their labor earnings in the household. Table 3.3 (rows 5-8) present the factor contributions from employment and earnings. Figure 3.7 displays the trends in employment (part-time and full-time) for people with and without disabilities. While the employment rates of people without disabilities remained steady from 1983 to 2011, the population of people with disabilities experienced noticeable declines in employment rates. Employment for those with disabilities fell from 35 percent employed in 1983 to 21 percent in 2011.



Source: Author's estimation from March CPS data.

Figure 3.7: Trends in the Employment of Working Aged Persons (18-64) with and without Disabilities

From 1983 to 1993 and from 1993 to 2004, declines in own employment accounted for a slowing of median income growth for people with disabilities of 0.77 percentage points and 1.05 percentage points, respectively. This slowed median income growth for those with disabilities due to declines in employment rates is in contrast to increased median income growth rates for those without disabilities. People without disabilities experienced increased median growth rates of 2.34 and 0.76 percentage points in the first to business cycles (1983-1993 and 1993-2004), respectively. Over the 2004 to 2011 business cycle, people without disabilities experienced negative growth in median incomes, and declines in own employment was the single largest contributor to this decline, accounting for 1.66 percentage points of negative growth. For those with disabilities, the contribution of own employment declines to slowing of median income growth was not as meaningful, accounting for a reduction in growth of 0.80 percentage points. Over the entire analysis period, employment of people without disabilities accounted for 1.29 percentage points of median income growth, while declines in the employment of people with disabilities accounted for a slowing of income growth by 3.65 percentage points.

A change in the employment of people with and without disabilities is highly correlated with changes in labor market earnings. Thus, this essay examines changes in median income due to changes in one's own labor earnings, conditional upon changes in their demographic characteristics: age, race, marriage, and own employment status. Over the first two business cycles, own earnings contributed to positive median income growth for both populations of people with and without disabilities. Over these first two business cycles, own earnings of people without disabilities accounted for 3.15 and 5.33 percentage points of the overall growth in median incomes. The population of people with disabilities experienced positive growth from own earning as well, accounting for 1.03 and 0.96 percentage points of positive growth in median incomes over the first two business cycles. These positive contributions to median income growth are in contrast to the declining share of income attributed to one's own labor earnings for people with disabilities (Table 3.2A). From 2004 to 2011, real incomes for both populations fell with own earnings contributing to some of the decline for those without disabilities, 0.46 percentage points. This slowing in the growth of median incomes of people without disabilities is in contrast to a small, but positive contribution of the own earnings factor for people with disabilities of .09 percentage points. Overall, from 1983 to 2011, own earnings contributed 7.50 percentage points of positive growth for people without disabilities, while this factor accounted for 1.99 percentage points of growth for those with disabilities.

Due to the correlation between one's own employment and earnings, the essay considers the contribution of own employment and earnings to income growth. Over the first two business cycles, own employment and earnings was responsible for 29 percent of median income growth from 1983 to 1993, and 31 percent from 1993 to 2004 for people without disabilities. This is substantially greater than the contribution of these factors to growth in median incomes of people with disabilities. These factors only accounted for 1 percent of income growth from 1983 to 1993, and 3 percent of growth from 1993 to 2004.

Next, this essay considers the contributions of the employment and earnings of others to median income growth for people with and without disabilities (Table 3.3, rows 7-8). Over the first two business cycles, the employment and earnings of other household members increased the growth rate in median incomes for both people with and without disabilities. Over the 2004-2011 business cycle, declines in the employments and earnings of others contributed to a slowing in the growth rate of median incomes for both populations. Employment and earnings of other household members contributed 7.93 and 8.44 percentage points to median income growth people without disabilities over the first two business cycles, while accounting for 1.28 percentage points of negative growth from 2004 to 2011. The positive growth over the first two business cycles attributed to the employment and earnings of other household members represents 42 percent of the overall growth in median incomes over both business cycles for people without disabilities. The importance of the employment and earnings of other household members for the population of people with disabilities is relatively volatile and varies greatly over each of the three business cycles analyzed. From 1983 to 1993, these factors accounted for 0.71 percentage points of median income growth.

And from 1993 to 2004 they were responsible for 6.99 percentage points of median income growth. Lastly, over the 2004-2011 business cycle these factors contributed 1.77 percentage points to the slowing of median income growth. The employment and earnings of other household members accounted for 3 percent and 22 percent of positive income growth over the first two business cycles, respectively.

The employment and earnings of other household members were jointly the largest contributor to median income growth for the population of people without disabilities, which is not the case for those with disabilities. Furthermore, the second largest joint positive contributor to income growth for people without disabilities were own employment and earnings. From 1983 to 2011, these four factors jointly were responsible for 64 percent of income growth for the people without disabilities, this is in comparison to those with disabilities, for which employment and earnings accounted for 26 percent of median income growth from 1983 to 2011. From 1983 to 2011, the highest share of gross mean income came from market income (own employment and labor earnings and the employment and earnings of other household members) which remained relatively constant for people without disabilities (Table 3.2B) while mean gross incomes increased. Thus, the largest factor responsible for growth in mean gross incomes was the growth in market income.

Next, this essay considers income from non-labor sources. These non-labor income sources are: private non-labor income (Table 3.3, row 9); receipt and generosity of SSI/DI (Table 3.3, rows 10-12); the value of other public health insurance accessed outside of SSI/DI (Table 3.3, row 13); other public cash and non-cash transfers outside of SSI/DI cash and health insurance benefits (Table 3.3, row 14); tax liabilities (Table 3.3, row 15); and the value of employer contributions to health insurance premiums (Table 3.3, row 16).

Private non-labor income accounted for 1.39, 0.21, and -1.27 percentage points of median income growth over the three business cycles for people without disabilities. Additionally, this factor accounted for -0.17, 0.34, and -1.11 percentage points of median income growth over the three business cycles for people with disabilities. Overall, this factor accounted for less than 1 percent of median income growth for the people without disabilities, and was responsible for a relatively small reduction in the growth of median incomes for people with disabilities.

Increases in the SSI/DI rolls for people with disabilities over each business cycle (Figure 3.5A) accounted for a small percentage point growth in income (Table 3.3, row 10). Overall, an increase in enrollment in these programs for people with disabilities was responsible for 5.38 percentage points (8 percent) of income growth from 1983 to 2011. The single largest contribution to growth in median incomes for people with disabilities over the first two business cycles was the value of health insurance obtained through SSI/DI (Medicare and/or Medicaid). Table 3.2A supports this finding by displaying the share of income attributed to the value of SSI/DI health insurance for people with disabilities increased from 5 to 18 percent of mean income from 1983 to 2011. The shift-share algorithm attributes 57 percent (14.08 percentage points) and 49 percent (17.21 percentage points) of income growth over the first two business cycles to growth in the value of SSI/DI health insurance for people with disabilities (Table 3.3, row 12), respectively. This is in stark contrast to the 4 percent attributed to this factor over the first two business cycles for people without disabilities. Figure 3.6 confirms this finding, and shows that the level and growth of insurance obtained through SSI/DI is greater than the level and growth in employer contributions to health insurance premiums. From 2004 to 2011, changes in the value of SSI/DI health insurance were estimated to contribute a small, but positive, increase to income growth for both populations. From 2004-2011 there was little change in the share of income attributed to

SSI/DI health insurance for both populations (Table 3.2 A and B). Over the entire analysis period, growth in the value of SSI/DI health insurance was responsible for 35.23 percentage points (53 percent of income growth) of income growth from 1983 to 2011 for people with disabilities and 2.61 percentage points (7 percent of income growth) of income growth for people without disabilities.

Cash benefits paid out to SSI/DI beneficiaries (Table 3.3, row 11) accounted for a small, but positive, increase in income growth for persons with disabilities. Of particular note is the fact that generosity in SSI/DI cash benefits was responsible for a slowing of income growth over the 2004-2011 business cycle for both populations. This could be due to a number of factors. For example, a change in the characteristics of SSI/DI beneficiaries coming onto the disability rolls, or the way in which SSI/DI cash benefits are calculated for new enrollees resulted in a decline in AIME due to the great recession (AIME is indexed to economy wide wage growth).

This essay additionally considers the receipt and generosity of SSI/DI jointly (summarized from Table 3.3). Over the three business cycles analyzed, increases in SSI receipt, generosity in payments, and the value of Medicare and Medicaid for people with disabilities were responsible for 18.04, 21.24, and -0.02 percentage points of income growth, respectively. Over the first two business cycles, SSI/DI accounted for 75 percent and 66 percent of all income growth for those with disabilities. The negative growth over the 2004 to 2011 business cycle for people with disabilities was due slower growth in SSI/DI cash benefits paid over the 2004-2011 business cycle relative to the growth over the previous two business cycles (Figure 3.6A).

The contributions to income growth of public health insurance obtained outside of SSI/DI channels (Table 3.3, row 13), other public cash and in-kind transfers other than health insurance (Table 3.3, row 14), and tax policy (Table 3.3, row 15) were low in every business cycle. Public health insurance has a positive effect on income growth over all business cycles for both populations. Other public transfers, varied in their contribution to income growth between populations and business cycles. Other public transfers slowed income growth for people without disabilities over the first business cycles, while it increased income growth for people with disabilities. Other public transfers then decreased both populations' incomes over the 1993 to 2004 business cycle, followed by increases in both population median incomes over the 2004 to 2011 business cycle. Tax policy affected those without disabilities more than those with disabilities. Overall changes in tax policy increased income growth from 1983 to 2011, with larger increases for people without disabilities.

The growth in the value of employer contributions to private health insurance (Table 3.3, row 16) increased median incomes for both populations over the first two business cycles and decreased median incomes for both populations in the last business cycle. The positive contributions over the first two business cycles were due to increases in the real value of employer contributions (Figure 3.6). The small, but negative contribution to income growth of this factor over the 2004 to 2011 business cycle was due to stagnation in the growth of employer contributions over this last business cycle (Figure 3.6).

Overall, the largest contributors to income growth for people without disabilities were employment and labor earnings, while the largest contributors to positive income growth for people with disabilities were the SSI/DI programs. The majority of growth in median incomes for people with disabilities was generated by real increases in the value of Medicare and Medicaid provided to SSI/DI beneficiaries. The level and growth in the value of these public insurance programs far outpaced the growth in employer contributions to health insurance, resulting in a closing of the median income gap between people with and without disabilities.

3.6 Conclusions and Discussion

This essay shows how dramatically levels and trends in the median income of working age people with disabilities increase both absolutely and in comparison to the median income of working age people without disabilities when the value of employer and government provided health insurance is included as income. The median income gap between people with and without disabilities has been closing over the past three decades, mostly due to increases in the value of public health insurance provided to SSI/DI beneficiaries. Using a shift share algorithm, this essay found that the SSI/DI programs (receipt, generosity in cash payments and the value of health insurance) were responsible for almost 70 percent of the total median income growth experienced by people with disabilities from 1983 to 2011. This is in contrast to people without disabilities, for which employment and earnings were responsible for almost 65 percent of median income growth.

Additionally, when the insurance value of health insurance is included, the share of people with disabilities in the bottom quintile of the working age population falls. The reduction in the fraction of people with disabilities in the bottom quintile resulted in an increase in the fraction of people with disabilities in the middle three quintiles. Thus, the make-up of the bottom quintile changes dramatically when a fuller measure of income including the value of health insurance is used.

This essay compared four alternative measures of income using the March CPS data: market income (all private sources of cash income); market and government income (all private and public sources of cash income); disposable income (market and government income plus the value of in-kind transfers except employer and government provided health insurance minus taxes); and disposable income plus health insurance (disposable income plus the insurance value of employer and government provided health insurance). Using these four measures, this essay was able to replicate the results from prior research which concluded that the income gap between persons with and without disabilities has been growing, thus leading to the conclusion that those with disabilities are relatively worse off now than they were three decades ago.

The conclusion from prior research that people with disabilities are relatively worse off today than they were thirty years ago is based on measures of income that include some government cash and in-kind transfers, while excluding the most valuable government in-kind transfer – health insurance. Including the value of government cash and in-kind transfers reflects the flow of resources available to individuals and their households. The value of Medicare and Medicaid is higher in level and in growth rate over time relative to employer premium contributions. In addition, there has been a growing fraction of disabled persons accessing Medicare and Medicaid benefits through the SSI/DI programs. Thus, any measure of income not including the resources accessed by people on Medicare, Medicaid, or employer sponsored insurance will underestimate the overall level of resources. Moreover, the income gap between those with and without disabilities will be overestimated due to disproportionally higher levels and growth rates in the value of Medicare and Medicaid relative to employer premium contributions, in addition to the growing fraction of disabled persons accessing Medicare and Medicaid benefits through the SSI/DI programs.

The essay argues that the fourth measure (disposable income plus health insurance) is a more appropriate measure of the flow of resources available to individuals and their households than the three other income definitions used in this essay. Using this more encompassing measure of income, this essay finds that the income gap between persons with and without disabilities has been closing over the past thirty years. This result signifies that people with disabilities have gained greater access to public health insurance, the value of which has been increasing rapidly. Thus, persons with disabilities have gained access to more health resources (increases in SSI/DI provided Medicare and Medicaid) resulting in higher government spending, overall and per-enrollee on SSI/DI beneficiaries.

The analyses presented in this essay serve to give researchers a better understanding of how sensitive income inequality results are to the definition of income. More recently, economists and the US Government have been concerned with measures of income that better capture the flow of resources to people and households, rather than focusing solely on labor or market income. This essay updates the results from the past literature by extending the use of these kind of measures to compare the overall flow of resources to people with and without disabilities. By replicating the results in the past literature regarding the income gap between persons with and without disabilities, this essay was able to show how important the inclusion of the value of public and private health insurance as income is to income inequality results.

REFERENCES

Aaron, H, and G. Burtless. 2014. *Potential Effects of the Affordable Care Act on Income Inequality*. Washington DC: Brookings Institution.

Acemoglu, D., and J. Angrist. 2001. “Consequences of Employment Protection? The Case of the Americans with Disabilities Act.” *Journal of Political Economy* 109(5): 915–957.

Armour, P., Burkhauser, R.V., & Larrimore, J. 2013. “Deconstructing Income and Income Inequality

Measures: A Crosswalk from Market Income to Comprehensive Income.” *American Economic Review: Papers & Proceedings*, 103(3): 173–177.

Atkinson, A. 1991. “Comparing Poverty Rates Internationally: Lessons from Recent Studies in Developed Countries.” *World Bank Economic Review*, 5(1): 3-21.

Atkinson, A.B. 1998. “Poverty in Europe.” Oxford: Wiley-Blackwell.

Atkinson, A.B. and A. Brandolini. 2001. “Promises and Pitfalls in the Use of Secondary Data Sets: Income Inequality in OECD Countries as a Case Study.” *Journal of Economic Literature* 39(3): 771–799.

Atkinson, A.B., T. Piketty and E. Saez. 2011. “Top Incomes in the Long Run of History.” *Journal of Economic Literature* 49(1): 3-71.

Auerbach, A.J. 1989. “Capital Gains Taxation and Tax Reform.” *National Tax Journal* 42(3): 391-401

Autor, D.H. and M.G. Duggan. 2003. "The Rise in the Disability Rolls and the Decline in Unemployment." *Quarterly Journal of Economics*, 118(1): 157-205.

Autor, D.H. and M.G. Duggan. 2006. "The Growth in the Social Security Disability Rolls: A Fiscal Crisis Unfolding." *Journal of Economic Perspectives*, 20(3): 71-96.

Autor, D.H. 2011. “The Unsustainable Rise of the Disability Rolls in the United States: Causes, Consequences, and Policy Options.” NBER Working Paper No. 17697.

Benítez-Silva, H., M. Buchinsky, H.M. Chan, S. Sheidvasser and J. Rust. 2004. "How Large Is the Bias in Self-Reported Disability?" *Journal of Applied Econometrics*, 19(6): 649-70.

Black, D., K. Daniel and S. Sanders. 2002. "The Impact of Economic Conditions on Participation in Disability Programs: Evidence from the Coal Boom and Bust." *American Economic Review*, 92(1): 27-50

Blank, R.M. 2011. “Changing Inequality.” Berkeley, CA: University of California Press.

Bound, J. and R.V. Burkhauser. 1999. "Economic Analysis of Transfer Programs Targeted on People with Disabilities." In *Handbook of Labor Economics.* Vol. 3C, ed. O. Ashenfelter and D. Card, 3417-528. Amsterdam: Elsevier Science North-Holland.

Bound, J., R.V. Burkhauser and A. Nichols. 2003. "Tracking the Household Income of SSDI and SSI Applicants." In *Worker Wellbeing and Public Policy.* 22, ed. S.W. Polachek. Amsterdam: Elsevier Science Ltd.

Bound, J. and T. Waidmann. 1992. " Disability Transfers, Self-Reported Health, and the Labor Force Attachment of Older Men: Evidence from the Historical Record." *The Quarterly Journal of Economics*, 107(4): 1393-1419.

Bound, J. and T. Waidmann. 2002. "Accounting for Recent Declines in Employment Rates among Working-Aged Men and Women with Disabilities." *Journal of Human Resources*, 37(2): 231-50.

Bureau of Labor Statistics. 2012. “Household Data Annual Averages: Employment status of the civilian non-institutional population 16 years and over by sex, 1973 to date.” Available at: http://www.bls.gov/cps/cpsaat2.pdf

Burkhauser, R.V., M.C. Daly and A.J. Houtenville. 2001. “How Working-Age People with Disabilities Fared over the 1990s Business Cycle.” In *Ensuring Health and Income Security for an Aging Workforce*, P.P. Budetti, R.V. Burkhauser, J.M. Gregory, and H.A. Hunt, eds. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Burkhauser, R.V., M.C. Daly, A.J. Houtenville and N. Nargis. 2002. "Self-Reported Work-Limitation Data: What They Can and Cannot Tell Us." *Demography*, 39(3): 541-55.

Burkhauser, R.V. and M.C. Daly. 2011. *The Declining Work and Welfare of People with Disabilities: What Went Wrong and a Strategy for Change*. Washington, DC: The AEI Press.

Burkhauser, R. V., S. Feng, S.P. Jenkins and J. Larrimore. 2011. “Estimating Trends in United States Income Inequality Using the March Current Population Survey: The Importance of Controlling for Censoring.” *Journal of Economic Inequality* 9(3): 393-415.

Burkhauser, R.V., S. Feng, S.P. Jenkins and J. Larrimore. 2012. “Recent Trends in Top Income Shares in the USA: Reconciling Estimates from March CPS and IRS Tax Return Data.” *Review of Economics and Statistics* 94(2): 371–388.

Burkhauser, Richard V. and Jeff Larrimore. 2009. “Using Internal CPS Data to Re-evaluate Trends in Labor-Earnings Gaps.” *Monthly Labor Review* August: 3-18.

Burkhauser, R.V., J. Larrimore and K. Simon. 2013. “Measuring the Impact of Valuing Health Insurance on Levels and Trends in Inequality and how the Affordable are Act of 2010 Could Affect Them.” *Contemporary Economic Policy,* 31(4): 779-794.

Burkhauser, R.V. and J. Larrimore. Forthcoming. “Median Income and Income Inequality: From 2000 and Beyond.” *U.S. 2010: America After the First Decade of the New Century,* J. Logan, ed. Russell Sage Foundation Press.

Burkhauser, Richard V., Ludmila Rovba, and Robert Weathers II. 2009. “Household Income.” Andrew J. Houtenville, David C. Stapleton, Robert R. Weathers II, and Richard V. Burkhauser (eds.), *Counting Working-age People with Disabilities: What Current Data Tell Us and Options for Improvement*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, pp. 143-190.

Burtless, G. 1999. “Effects of Growing Wage Disparities and Changing Family Composition on the U.S. Income Distribution.” *European Economic Review* 43(4-6): 853–865.

Burtless, G. 2010. “Crisis No More: The Success of Obama’s Economic Stimulus Program.” *Pathways Magazine* Summer, 24-28.

Charles, K.K. 2003. "The Longitudinal Structure of Earnings Losses among Work-Limited Disabled Workers." *Journal of Human Resources,* 38(3): 618-46.

Congressional Budget Office (CBO). 2010. “CBO’s 2010 Long-Term Projections for Social Security: Additional Information (October).” Washington DC: U.S. Government Printing Office.

Congressional Budget Office (CBO). 2012. “The Distribution of Household Income and Federal Taxes, 2008 and 2009.” Washington DC: U.S. Government Printing Office.

Congressional Budget Office (CBO). 2013. “The Distribution of Income and Federal Taxes, 2010.” Washington, DC: U.S. Government Printing Office.

Daly, M.C. and R.V. Burkhauser. 2003. “The Supplemental Security Income Program.” In *Means Tested Transfer Programs in the United States,* R. Moffitt, ed. Chicago: University of Chicago Press, NBER Conference Report Series.

Daly, M. C. and R.G. Valletta. 2006. “Inequality and Poverty in the United States: The Effects of Rising Dispersion of Men’s Earnings and Changing Family Behavior.” *Economica* 73(289): 75–98.

Deaton, A. 1997. “The Analysis of Household Surveys: A Microeconometric Approach to Development Policy.” Baltimore, MD: Johns Hopkins University Press.

DeNavas-Walt, C., B.D. Proctor and J.C. Smith. 2008. “Income, Poverty and Health Insurance Coverage in the United States: 2007.” U.S. Census Bureau Current Population Reports, 60-235. Washington, DC: Government Printing Office.

DeNavas-Walt, C., B.D. Proctor and J.C. Smith. 2013. *U.S. Census Bureau, Current Population Reports P60-245, Income, Poverty, and Health Insurance Coverage in the United States: 2012*. Washington, DC: U.S. Government Printing Office.

d’Ercole, M.M. and M. Förster. 2012. “The OECD Approach to Measuring Income Distribution and Poverty: Strengths, Limits and Statistical Issues.” In *European Measures of Income and Poverty: Lessons for the U.S.*, D.J. Besharov and K.A. Couch, eds. New York, NY: Oxford University Press.

Feenberg, D. and E. Coutts. 1993. "An Introduction to the TAXSIM Model." *Journal of Policy Analysis and Management* 12(1): 189–94.

Gottschalk, P. and T.M. Smeeding. 1997. “Cross-National Comparisons of Earnings and Income Inequality.” *Journal of Economic Literature* 35(2): 633–687.

Gottschalk, P. and S. Danziger. 2005. “Inequality of Wage Rates, Earnings and Family Income in the United States, 1975–2002.” *Review of Income and Wealth* 51(2): 231–254.

Hotchkiss, J.L. 2003. *The Labor Market Experience of Workers with Disabilities: The ADA and Beyond*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research.

Hotchkiss, J.L. 2004. “A Closer Look at the Employment Impact of the Americans with Disabilities Act.” *Journal of Human Resources* 39(4): 887–911.

Houtenville, A.J. and R.V. Burkhauser. 2005. “Did the Employment of Those with Disabilities Fall in the 1990s and Was the ADA Responsible? A Replication of Acemoglu and Angrist (2001)—Research Brief.” Ithaca, NY: Cornell University, Research and Rehabilitation Training Center for Economic Research on Employment Policy for Persons with Disabilities.

Houtenville, Andrew J., David C. Stapleton, Robert R. Weathers II, Richard V.Burkhauser (eds.) *Counting Working-age People with Disabilities: What CurrentData Tell Us and Options for Improvement*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, (2009).

Iceland, J. 2003. “Why Poverty Remains High: The Role of Income Growth, economic Inequality, and

Changes in family Structure, 1949-1999.” *Demography* 40(33): 499-519.

Interagency Technical Working Group. 2010. "Observations from the Interagency Technical Working Group on Developing a Supplemental Poverty Measure (2010)." Available at: http://www.census.gov/hhes/www/poverty/SPM_TWGObservations.pdf

Jolls, C. and J.J. Prescott. 2005. "Disaggregating Employment Protection: The Case of Disability Discrimination." Harvard Public Law Working Paper no. 106. Cambridge, MA: Harvard Law School.

Larrimore, J., R.V. Burkhauser, S. Feng and L. Zayatz. 2008. "Consistent Cell Means for Topcoded Incomes in the Public Use March CPS (1976–2007)." *Journal of Economic and Social Measurement* 33(2-3): 89–128.

Larrimore, J., R.V. Burkhauser and P. Armour. 2013. "Accounting for Income Changes over the Great Recession (2007-2010) Relative to Previous Recessions: The Importance of Taxes and Transfers." NBER Working Paper No. 19699.

Larrimore, J. Forthcoming. "Accounting for United States Income Inequality Trends: The Changing Importance of Household Structure and Male and Female Labor Earnings Inequality." *Review of Income and Wealth*.

Meyer, B.D. and W.K.C. Mok. 2013. "Disability, Earnings, Income and Consumption." NBER Working Paper No. 18869.

Meyer, B.D. and J.X. Sullivan. 2003. "Measuring the Well-Being of the Poor Using Income and Consumption." *The Journal of Human Resources* 38: 1180-1220.

Nazarov, Z. and C.G. Lee. 2012. "Disability statistics from the Current Population Survey (CPS)." Ithaca, NY: Cornell University Rehabilitation Research and Training Center on Disability Demographics and Statistics. Available at: www.disabilitystatistics.org.

Piketty, T. and E. Saez. 2003. "Income Inequality in the United States, 1913–1998." *Quarterly Journal of Economics* 118(1): 1–39.

Short, K. 2012. *U.S. Census Bureau Current Population Reports P60-244.The Research Supplemental Poverty Measure: 2011*. Washington, DC: U.S. Government Printing Office.

Roine, J. and D. Waldenstrom. 2012. "On the Role of Capital Gains in Swedish Income Inequality." *Review of Income and Wealth* 58(3): 569-587.

Ruggles, P. 1990. *Drawing the Line: Alternative Poverty Measures and their Implication for Public Policy*. Washington, DC: Urban Institute Press.

Ryscavage, P. 1995. "A Surge in Growing Income Inequality?" *Monthly Labor Review*, 118(8): 51–61.

Social Security and Medicare Boards of Trustees. 2010. "Status of the Social Security and Medicare Programs: A Summary of the 2010 Annual Reports." Washington, DC (August). Available at www.ssa.gov/oact/trsum/index.html.

Social Security and Medicare Boards of Trustees. 2013. "A summary of the 2013 annual reports: Social Security and Medicare boards of trustees." Social Security Administration, Baltimore, MD.

Sommers, B.D., & D. Oellerich. 2013. "The Poverty Reducing Effect of Medicaid." *Journal of health economics*, 32(5), 816-832.

Stapleton, D.C. 2011. "Bending the employment, income, and cost curves for people with disabilities." Center for Studying Disability Policy, Washington DC.

Stern, Steven. 1989. "Measuring the Effect of Disability on Labor Force Participation." *Journal of Human Resources*, 24(3): 361-95.

Stewart, K.J. and S.B. Reed. 1999. "CPI Research Series Using Current Methods, 1978-98." *Monthly Labor Review* 122(6): 29-38.

Weathers, R. II and D. Wittenburg. 2009. "Employment." Andrew J. Houtenville, David C. Stapleton, Robert R. Weathers II, and Richard V. Burkhauser (eds.), *Counting Working-age People with Disabilities: What Current Data Tell Us and Options for Improvement*. Kalamazoo, MI: W.E. Upjohn Institute for Employment Research, pp. 101-145.

Weinberg, D.H. 2006. "Income Data Quality Issues in the CPS." *Monthly Labor Review* 129(6): 38-45.

World Bank. 2001. "World Development Report 2000/2001Attacking Poverty." The World Bank: Washington D.C.