The Dissertation Committee for Can Cui
certifies that this is the approved version of the following dissertation:

Essays on Public Finance and Health Economics

Committee:

Marika Cabral, Supervisor

Michael Geruso

Dayanand Manoli

Todd Olmstead

Clemens Sialm

Essays on Public Finance and Health Economics

by

Can Cui, B. Eco.; M.S. Econ.

DISSERTATION

Presented to the Faculty of the Graduate School of

The University of Texas at Austin

in Partial Fulfillment

of the Requirements

for the Degree of

DOCTOR OF PHILOSOPHY

THE UNIVERSITY OF TEXAS AT AUSTIN

May 2016

Acknowledgments

First and foremost I wish to acknowledge the guidance and supervision of my adviser, Marika Cabral, along with the rest of my dissertation committee, Day Manoli, Mike Geruso, Clemens Sialm, and Todd Olmstead. I won't be the researcher I am today without their advice and support.

Next, I am immensely thankful to my family. My parents have given me unconditional love and encouragement in countless ways for my entire life. My younger brother has been an inspiration to me and brought lots of laughter into my life. My grandmother, who taught me to read and count before I started kindergarten, has always been my role model for her perseverance and kindness.

Finally, I wish to acknowledge all my friends and cohort peers at the University of Texas for filling coffee breaks with interesting conversations. Mengyuan, Yaoyao, Rongzhang, Hao, Ye, and many other friends have kindly kept me company during ups and downs of life in graduate school.

Essays on Public Finance and Health Economics

Publication No. ____________________

Can Cui, Ph.D.
The University of Texas at Austin, 2016

Supervisor: Marika Cabral

This dissertation examines several questions in public finance, including health care, workers' compensation program, and tax rebates. The first chapter, entitled, "Financial Incentives and Physicians Behavior: Evidence from Texas Workers Compensation Medical Claims", examines whether financial incentives influence the quantity and composition of medical care provided by physicians. I study this question by leveraging an administrative change in the maximum allowed reimbursement rates for surgical services performed in a hospital setting for Texas Workers' Compensation medical claims. I document evidence of strong substitution in the location of care, indicating that many surgical services can be provided in either a hospital or office setting. I find that the 2% increase in surgical services provided in a hospital setting in response to this reform is fully offset by reduced utilization in an office setting. I also find that nonsurgical services performed in a hospital increased in response to the reform, suggesting surgical and nonsurgical services are complements with respect to physician financial incentives. More generally, my results suggest that the location of care is responsive to financial incentives, and an optimal payment policy should account for substitution along this margin.

The second chapter, entitled "Cash-on-Hand and Demand for Credit", examines the effect of tax rebates on demand for small dollar credit loans. Subprime consumers often use small dollar credit to meet short-term financial needs over pay cycles. However, relatively little is known about the income sensitivity of demand for credit in this market. This chapter provides a causal estimate of the effect of tax rebates on the demand for small dollar credit, using shocks from the Earned Income Tax Credit (EITC) benefits and a unique proprietary loan-level dataset. The results show that a $100 increase in EITC benefits leads to a 8.3% in the number of loan applications and a 6.6% reduction in the number of borrowers. This could translate into sizable reductions in loan volume and savings in financial charges. The estimates are robust to various specifications checks. The results further indicate that EITC recipients are liquidity constrained. More broadly, the results suggest that public programs with income benefits could help recipients with consumption smoothing in the presence of credit market frictions.

The third chapter, entitled "Take-up of Workers' Compensation Insurance in Texas", is coauthored with Marika Cabral and Michael Dworsky. This chapter examines how employers choose to provide benefits for their workers. Workers' compensation program is a large government program which provides monetary and medical benefits to injured workers. Texas is currently the only state that allows voluntary participation. Using difference-in-differences variation in regulated manual premium, this paper empirically analyzes employers' take-up of workers' compensation insurance coverage. We find that 10% increase in regulated premium reduces the number of covered firms by 2%, with similar effect on covered payroll.

Table of Contents

List of Tables

List of Figures

Chapter 1

Financial Incentives and Physicians' Behavior: Evidence from Texas Workers' Compensation Medical Claims

1.1 Introduction

Insurer reimbursement for a particular medical service often depends on the location in which the service is provided. The same service is often paid at a different rate depending on whether that service was provided at physicians' offices or within a hospital outpatient department. For example, in 2014 Medicare paid three times more for a level IV nerve injection when performed in a hospital than for the same service performed in a freestanding physician's office. This variation in payments raises questions about how these differential payments across locations of care affect the supply of medical services. In order to optimally design medical reimbursement schedules, it is important to assess whether and how much physicians respond to these differential payments by shifting the location of the care they provide.

This paper explores the impact of differential payments by location of care within the setting of the Texas' Workers Compensation system. Using administrative medical claims data, I examine the effect of a sharp increase in the maximum reimbursement rate for surgical services provided within a hospital setting on the quantity and composition of medical services across different locations of care.

In 2008, Texas increased the maximum reimbursement rates for surgical services performed in a hospital setting by 25% for Workers' Compensation medical claims. Taking advantage of this legislated change in allowable reimbursement rates, I document a strong first-stage effect on the average per patient payment to physicians. This analysis reveals that the average payment per patient increased by 6% for surgical services as a result of the change in the maximum allowable reimbursement rate. I then leverage this induced variation in payments to estimate the effect on the quantity and composition of medical care provided.

My analysis reveals that surgical services performed within a hospital setting increased by 2% in response to the payment increase. However, I find that this increase was fully offset by a decline in the number of surgical services provided within an office setting, meaning that the reform had no impact on the total quantity of surgical services provided. These results suggest strong substitution in the location of care among surgical procedures, and this pattern is robust to the inclusion of service fixed effects.

Further, I investigate the impact on nonsurgical services, which are not explicitly targeted by the reform but may have been indirectly affected. I find the quantity of nonsurgical services provided in a hospital increased by 4% in response to this policy change, indicating that surgical services and nonsurgical services are complements. In addition, I document heterogeneity in this effect among nonsurgical services which illustrates that the effect is strongest for those nonsurgical services that are typically provided alongside surgical services. Accounting for these substitution patterns, my results suggest that the overall effect of this reform was an increase in the total quantity of medical care by 4.5% on average, where most of this increase comes from an increase in complementary nonsurgical services provided within a hospital setting.

More generally, my results indicate that it is important to account for complements and substitutes when evaluating the effect of a change in reimbursements. While some prior studies have investigated demand side complementarities based on changes in patient cost-sharing (e.g., Cabral and Cullen 2011; Philipson and Goldman 2007; Chandra et al. 2010; Brot-Goldberg et al. 2015), there has been little evidence on supply side complementarities based on changes in physician reimbursements. This paper contributes to the existing literature by documenting meaningful supply side complementarities in the location that care is provided and in the types of services performed. The empirical findings of this paper suggest that the design of medical fee schedules could be a useful policy tool to influence the location in which care is provided.

The rest of the paper is organized as follows. Section 1.2 discusses the related literature. Section 1.3 describes the institutional setting and data. Section 1.4 discusses the empirical strategy and identification assumptions. Section 1.5 shows the empirical analysis. Finally, section 1.6 concludes.

1.2 Related Literature

This paper contributes to several areas of prior literature. Much of the prior literature on physician financial incentives has focused on whether the supply curve for physicians' services is upward sloping or backward bending. McGuire and Pauly (1991) develop a comprehensive theoretical model of physician behavior that accommodates both inducement behavior and profit maximization, and also recognizes that physicians provide services to multiple markets.[1] Recent studies (e.g., Hadley and Reschovsky 2006; Mitchell et al. 2000; Hadley et al. 2001; Clemens and Gottlieb 2014) that incorporate elements of the McGuire-Pauly model find the supply of Medicare services is positively related to Medicare payment, but inversely related to payments for competing or substitute services. My analysis in this paper reveals a small positive price elasticity of supply of medical care, supporting the upward-sloping supply curve. The estimated elasticity of supply of medical care in the present context is smaller than the elasticity estimated in Clemens and Gottlieb (2014), who use changes in payments across-the-board for all services. Among the many possible explanations for this difference in magnitudes across the different settings, substitution between alternative locations for providing care may explain the smaller effects I find in this context.

This paper also extends the line of research on physician incentives further by analyzing whether the location of care is responsive to financial incentives. The location of

[1] Another important insight delivered by McGuire and Pauly (1991) is the interdependence of the markets for medical services when there is more than one potential payer. This interdependence was highlighted in a recent study by Heaton (2012) on the effects of the 2006 Massachusetts healthcare reform. Heaton's research shows that the billing of emergency room visits to workers compensation is related to the availability of Medicaid. Powell and Seabury (2013) find that the reduction in medical care generosity for work-related injuries affect post-injury earnings, especially for workers with lower back injuries. This study does not account for interdependence between Workers' Compensation and other payers, such as private group health insurance, Medicare, or Medicaid. The medical services delivered in the context of Workers' Compensation is not a significant proportion of total business. The Workers' Compensation system overall accounts for only 2% of medical expenditures in the economy in 2012. In 2012, workers' compensation medical payments benefits paid (excluding cash benefits) totaled about \$30.9 billion (Sengupta et al., 2014). In comparison, total cost of medicare is about \$566.44 billion, and national health expenditures is \$2.79 trillion in 2012, according to statistics from CMS. Therefore, in the absence of micro-level data covering all-payer claims, there is little prospect of uncovering spillovers of fee schedule changes into other channels of provision of medical services. For the purpose of quantifying the effect of Workers' Compensation fee schedule changes on the price level and the consumption of medical services provided by physicians in the context of Workers' Compensation, disregarding such potential spillovers does not compromise the findings.

care is an important factor in the design of medical fee schedule, given regulatory concerns regarding outpatient surgery (Quattrone, 2000) and payment variations across settings (Wynn et al., 2008). The empirical analysis in this paper fits within McGuire and Pauly (1991)'s model that has with multiple services (or locations) and one payer. I find providers are vary elastic in the location they provide care, suggesting that it is necessary to take into account behavioral responses along this margin when researchers evaluate the effects of medical fee schedules changes on total medical spending.

Another contribution of this paper is to extend the prior literature on physician financial incentives by examining a setting in which there may be supply-side complementarities. My results suggest that surgical and non-surgical services are complements with respect to provider reimbursement. Prior studies have focused on the demand-side complementarities based on changes in patient cost-sharing (e.g., Cabral and Cullen 2011; Philipson and Goldman 2007; Chandra et al. 2010). This paper provides direct evidence of supply-side complementarities in the types of services performed by leveraging changes in physician reimbursements for surgical services and estimating the effect on both surgical and non-surgical services.

Lastly, this paper also contributes to the small body of existing research studying Workers' Compensation reimbursement schedules. Most of the prior research on medical fee schedules within Workers' Compensation are based on case studies (e.g., Schmid and Lord 2012; Corro and Robertson 2011). In contrast, this paper leverages a large legislated change in reimbursements to examine the effect on the composition and location of care provided within a large Workers' Compensation program.

1.3 Background and Data

1.3.1 Texas Workers' Compensation

Workers' Compensation (WC) is a state-regulated insurance program that pays medical bills and replaces partial lost wages for employees with work-related injuries or illnesses. It also protects covered employers from potential civil suits brought by injured workers. In Texas, it is not mandatory for all employers to carry occupational injury insurance coverage.[2] Employers could choose to purchase worker compensation insurance policies to cover income benefits and medical benefits for work-related injuries.

The Texas Workers' Compensation law lists four types of benefits: income, medical, death, and burial. Income benefits replace a portion of the wages a worker loses because of a work-related injury or illness and provide compensation for permanent impairment to a worker's body.[3] Medical benefits pay for any medical care that is reasonable and necessary to treat a work-related injury or illness. The employer's Workers' Compensation insurance company pays medical benefits directly to the physician or healthcare provider who treated the injured worker. Except in an emergency, the injured worker chooses the treating doctor, who must approve all medical care for an injury or illness.[4]

[2] Private sector employers have been allowed the option of choosing to purchase workers' compensation insurance since 1913. Texas is currently the only state that allows any private-sector employer the option of not purchasing WC insurance or become "nonsubscribers" to the state WC system. There are, however, still some exceptions, such as construction contracts for governmental entities; in such cases, the insurance requirements are mandatory. Several states' laws have exceptions that allow small private sector employers to opt out of coverage.

[3] The four types of income benefits are temporary income benefits, impairment income benefits, supplemental income benefits, and lifetime income.

[4] Currently, injured workers in Texas have the ability to select their own initial treating doctor. In turn, the treating doctor provides medical care to the injured worker and submits those bills to the employer's insurance carrier for payment. The insurance carrier has the ability to review the medical necessity of treatments provided to injured workers and pays medical bills in accordance with the fee guideline established

The Texas Workers' Compensation system was designed as a fee-for-service system which allows healthcare providers to submit bills and receive payment for each service they deliver to injured workers without the use of pre-paid case rates, co-payments, deductibles or co-insurance arrangements.[5] For injured workers, there is no out-of-pocket costs for claiming medical benefits.

In 2008, the total payroll covered by workers' compensation was $270 billion and the total premium paid was $2.62 billion. Medical costs make up more than 65% of Workers' Compensation costs in Texas. For more than 90% of the medical claims, patients received at least one professional service. During the period studied in this paper, professional costs have increased steadily, and make up more than 50% of total medical costs for Workers' Compensation claims (TDI, 2014).

In this paper, I focus on medical benefits and reimbursement rates for professional services provided by physicians. The maximum allowed reimbursement rates (MAR) for physicians for Workers' Compensation claims are set based on the reimbursement rates for

---

by the TWCC. Disputes over medical payments or the medical necessity of treatments are handled administratively through the TWCC. When a patient visits a medical office for the first time, it is important for the physician to determine if any injury or illness is work-related. If the patient's injury or illness is work-related, the physician's office should determine if the employer has Workers' Compensation coverage. If the coverage is under the Texas Workers' Compensation system, then the physician must follow the statute, rules, and guidelines of the state of Texas. These rules mandate reporting requirements, pre-authorization of certain procedures and services, prescribed billing forms, and specific time frames for filing. Workers' compensation law and rules also define different roles for doctors, how the physician's examination impacts the injured workers' income benefits, and the expected reimbursement for healthcare services.

[5] The Texas Workers' Compensation Commission (TWCC) administers the Texas Workers' Compensation Act and is mandated to adopt specific administrative rules, including the Medical Fee Guidelines. An important medical cost-control mechanism in many states is the physician fee schedule, which specifies maximum allowable reimbursements for specific medical services provided to treat WC claimants. Most states use such fee schedules to regulate payments to doctors and there is a substantial body of research to document that fee schedules are effective in controlling WC medical costs.

Medicare.[6] For professional services, the Resource-Based Relative Value Scale (RBRVS) is used, in which payments for services are determined by the resource costs needed to provide them.[7] The cost of providing each service is divided into three components: physician work, practice expense, and professional liability insurance. Payments are calculated by multiplying the combined costs of a medical service by a conversion factor. The conversion factor used for Texas Workers' Compensation claims is set as a scaling factor times the Medicare conversion factors for all medical services. Specifically, in area *a*, for service *j* in year *t*, payment is given as:

$$MAR_{ajt} = Conversion\ Factor_t \times RVU_j \times Geographic\ Adjustment\ Factor_a$$

The Relative Value Units (RVUs) associated with each service are intended to measure the resources and costs required to provide that service. RVUs are constant across areas while varying across services.[8] Payments are also adjusted for geographical differences in resource costs using the Geographic Adjustment Factor.

From March 2008, there was an 25% increase in the conversion factor for ***surgeries*** performed in ***facility*** settings. Table 1.2 shows the conversion factor over time and by place and type of services. This change in the conversion factor means there was a 25% proportional change in the maximum allowed reimbursement rates. It is worth empha-

[6] Although the payers for workers compensation medical benefits are mostly private insurers, the maximum allowed reimbursement rates are regulated by the Texas Department of Insurance.

[7] The fee schedule assigns a fixed Relative Value Units (RVUs) to each medical service, which are determined according to the Resource-Based Relative Value Scale (RBRVS), initially developed by Hsiao et al. (1988).

[8] The conversion factor is a multiplier that is determined by the Centers for Medicare and Medicaid Services (CMS) to convert the quantity of care to monetary amount. It is updated annually.

sizing that this policy change is on the maximum amount of reimbursement allowed for Workers' Compensation claims, not the actual amount paid to providers. The maximum reimbursement rates are binding for insurers and providers who do not have any existing agreement, which makes up about 84% of all medical claims. Insurers can negotiate with hospitals and physicians to pay lower than this regulated rate. The relationship between the fee schedule amount and the market price for the medical service can affect the degree to which administrative changes in reimbursement affect provision of care.[9] In the section of empirical analysis, I analyze the impact of this policy change on the actual amount paid to providers as a first stage.

1.3.2 Data

Data for this project comes from multiple sources. The primary data is medical claims public use files on professional services from Texas Department of Insurance (TDI). Medical claims submitted from 2005 to 2012 are used for this analysis.[10] The data set excludes transactions and payments associated with medical services provided by hospitals and ambulatory surgical centers but includes transactions related to services delivered by physicians at these places of service. These claim-level data contain rich information on medical diagnosis and treatment for patients and are likely to be highly accurate and

[9] Because WC reimbursements for medical services are not necessarily at the fee schedule amount, the changes in WC reimbursements are not always strictly proportional to fee schedule changes. When a state fee schedule is changed for a specific service, the percentage change in WC reimbursements for that service could be similar to, smaller than, or even larger than the percentage change in the fee schedule.

[10] Claims prior to 2005 are not publicly available. Though medical claims from early 2013 are available, there is some lag in processing claims data and claims could go through revisions or adjustments by insurers after submission. To have comparable medical claims and minimize the problem of truncations, claims from 2013 are excluded from analysis.

complete, as claims are directly reported by WC insurers.[11]

As typical in medical claims data sets, we have data on medical information including HCPCS/CPT codes, ICD-9 codes, place of service, the total amount charged, the total amount paid, date of service, provider information, including address, license number, and NPI, and patients' characteristics, such as date of injury, date of birth, mailing address, and employer's location. I rely on the HCPCS/CPT codes to classify medical services into surgical and nonsurgical services and use place of services codes to define facility and nonfacility settings.[12]

To supplement the medical claims data, I also use Physician Masterfile from Texas Medical Board, a registry of all physicians licensed to practice in Texas, to obtain more detailed characteristics on providers, such as their primary and secondary specialty, age, and location. This masterfile can be matched with claims data using physicians' state license numbers.[13]

[11] Overall, less than 5% of claims are disputed, according to statistics from TDI. These data are updated each month and reflect the resolution of any disputed claims.

[12] See the appendix A.1 on data construction for more details.

[13] Data on treatment and return-to-work guidelines from Official Disability Guidelines (ODG) is also used to understand the recommended courses of treatment and average duration of injuries for injured workers. Information on premiums of Workers' Compensation insurance in Texas and at the national level are from the Oregon Department of Consumer and Business Services. Aggregated data on medical benefits and income benefits for Workers' Compensation claims was obtained from TDI under The Public Information Act.

1.3.3 Summary Statistics

Table 1.1 shows the classification of place of services. In most cases, facility means in a hospital setting, while nonfacility refers to an office setting.[14] Hospitals, including outpatient, inpatient, and emergency room visits, make up for 76% of the visits to facilities. Physicians' offices, combining offices and health clinics, make up for 62% of the visits to nonfacility settings.

At the medical bill level, most bills are for nonsurgical services (95.91%). Among nonsurgical services, 93% of the procedures are performed in nonfacility settings, such as physician's office.[15] Among surgical services, more than half (58%) are performed in facility settings, such as hospital. Payment is set differently for facility and non-facility settings to compensate for differential costs and risks.[16]

Table 1.3 lists the five most common surgical and nonsurgical services. Common surgical services include injections, venipuncture, etc. Common nonsurgical services include mostly office visits and therapeutic activities. Surgical services are not necessarily complicated or risky surgeries. Some of the surgical services with high volumes are diagnostic and non-invasive types of treatment.[17] The average cost and share in facility vary

[14] Classification of place of services is based on CMS. For details on place of services, see this listing from CMS.

[15] Throughout this paper, a claim means a unique work-related injury or illness for an employee. Each claim can have multiples bills submitted during the course of treatment. For each bill, if more than one service is provided, there could be multiples lines. Each line represents a distinct type of service.

[16] A service or procedure is defined by HCPCS Level I (or CPT) codes. Throughout this paper, the term "service" and "procedure" are used interchangeably. Both refer to the HCPCS (or CPT) code, as a measure of unit of medical care.

[17] Common invasive surgical services include arthrodesis and laminectomy. Examples for less invasive surgical services include sutures and debridement procedures.

across medical services from less than 1% to 85%. It is worth noting that even for nonsurgical services, there are substantial share of medical procedures performed in facility for some nonsurgical medical services, such as blood count (52%) and radiologic examination (19%). Nonsurgical services are on average less expensive than surgical services. Testings, such as blood count and radiologic exams, cost around $10, while injections can cost more than $200.

To provide some context about the typical medical treatment for worker compensation claims, table 1.4 presents the summary statistics from Workers' Compensation medical claims data. On average, there are 2.9 million medical claims and about 163,431 employees filing for Workers' Compensation claims each year. The average duration of treatment for injured workers is about 26 days. The average amount paid per claim is about $231, which is less than half of the total amount charged.[18] The WC payments to physicians is more generous than Medicare payments, but less generous compared to private group health insurance.

1.4 Empirical Strategy

As described previously, the Texas Workers' Compensation system increased the maximum allowed reimbursement for surgical services in a hospital setting by 25% starting in March 2008. I first show that the actual payment to providers increased as a result of the administrative increase in reimbursement policy, as a first stage. Then I examine

[18] Cost of medical claims, if covered by Workers' Compensation insurance, are paid by insurers to providers. The charged amount is submitted by healthcare providers. Amount charged might not accurately reflect the true costs of medical treatment.

the impact on total quantity of surgical services by location of care received by injured workers. I also investigate possible spillover effects for nonsurgical services, which are not directly impacted by this policy.

1.4.1 Estimating Equations

To investigate the impact on the composition of care received by patients, I compare outcomes for workers who started their worker compensation medical claims at different points in time. For example, workers who started treatment in early 2007 are not affected by the policy change. However, workers who are otherwise similar but started treatment in June 2008 are affected.

Before presenting the estimation equations, I first define the measure of price and quantity of medical care, which are used as outcome variables in the empirical analysis. For the outcome variable in the first-stage analysis, I calculate the average payment per patient for patient i who started medical claims in year t of as follows:

$$Price_{it} = \sum_j RVU_{ijt_o} P_{jt} \tag{1.1}$$

For the quantity of medical services, I calculate the total quantity of medical services per patient for patient i who started medical claims in year t as follows:

$$Quantity_{it} = \sum_j RVU_{ijt} P_{jt_o} \tag{1.2}$$

where j is the index for each distinct type of medicare service (identified by HCPCS code in data), i is the index for each patient, t is the index for the year when the patient first started treatment. RVU_{ijt} is the total units of RVUs for medical service j for patient i in year t, and P_{jt} is the average price per RVU for medical service j in year t.[19] When I look specifically at the price or quantity of a subset of medical services **s**, for example, surgical services, I will restrict the summation to the set where medical services j belong to the specific subset **s** (i.e., $j \in \mathbf{s}$).

For the measure of price, I fix the quantity and composition of medical service at base year t_o (RVU_{ijt_o}) and use the price of medical services at year t (P_{jt}) to construct the average payment per patient. This measure of price allows costs to change as reflected in claims data and is independent of any potential changes in the total quantity and composition of medical care over time. For the total quantity of medical services, I fix the price of medical services at base year t_o (P_{jt_o}) and allow the quantity and composition of medical service (RVU_{ijt}) to change over time. This quantity measure could be interpreted as a dollarized amount of medical services received per patient. For simplicity, I will refer to this quantity measure as the total RVUs in later sections.

To investigate the effects of physicals payments on the composition of medical care provided, I estimate the following specification:

$$Y_{it} = \sum_{t \neq 2007} \beta_t \mathbb{1}_t + \alpha X_{it} + \theta Interim_t + \epsilon_{it} \tag{1.3}$$

where i is the index of distinct medical treatment episodes for injured workers, t is the index of time (measured by the year of the first claim) and β_t is the year fixed

[19] For medical services performed in facility, I also include hospitals costs for those medical service. I calculate the average cost for each medical service from the institutional claims data and convert that cost in dollars to RVUs.

effects. Year 2007 is omitted. $Interim_t$ is an indicator for workers who started treatment from December 1, 2007 to February 29, 2008, to allow the possibility that they are partly affected by the policy change during the course of treatment. X_{it} is a set of individual-level control variables, including the patient's age, gender, county of residence, and whether his or her first visit was to an emergency department. Y_{it} is the outcomes variable of interest, the average payment per patient or the total RUVs per patient per episode defined previously.[20] The key parameter of interest is β_t, which can be interpreted as the change in the costs paid or the quantity of care received by injured workers due to the administrative increase in reimbursement policy.

I also estimate the following specification including service fixed effects:

$$Z_{jpt} = \sum_{t \neq 2007} \beta_t \mathbb{1}_t Facility_p + \alpha_t \mathbb{1}_t + \theta_j \mathbb{1}_j + \delta_s Facility_p + \epsilon_{jpt} \tag{1.4}$$

where t is the index of time (measured by year), j represents the type of services, and p is the index for locations of care (in a hospital setting or in an office setting). $Facility_s$ is an indicator for services performed in a hospital setting, α_t is the year fixed effects, θ_j is service fixed effects, and β_t is the set coefficients for interaction terms between the facility dummy and year dummies. Year 2007 is omitted. The main analysis uses the log of total number of surgical services per patient as Z_{jpt}.[21] The key parameter of interest is β_t, which can be interpreted as the difference in the outcome variable over

[20] I limit the quantity of medical services to the first three months of each episode to avoid possible truncation problems for medical treatment.

[21] I scale this measure to the total number of medical services per 100,000 patients when using log as the outcome variables to avoid dealing with very small numbers.

time in a hospital setting versus in an office setting. If the identification assumption holds and the policy change is exogenous, estimates of β_t for time periods before 2008 should be small and insignificant. The estimates of β_t after year 2008 would show us the substitution of surgical services between hospital and office. If physicians respond to higher payment by providing more care in a hospital setting, we would see more surgical services performed in a hospital setting after 2008, compared to surgical services performed in an office setting.

The specification in equation 1.3 does not account for potential changes in the mixes of the types of medical services received by injured workers over time. The alternative within-service comparison specification allows me to compare the quantity of medical care within service by including service fixed effects and explore heterogeneity across different types of medical services.

1.4.2 Identification

This paper takes advantage of an administrative change in maximum allowed reimbursement rates for certain types of medical services in March 2008. For the identification to be valid, the change in regulations on reimbursement has to be orthogonal to other factors that could potentially affect supply of medical care. Specifically, workers who started their worker compensation claims before or after the policy change should be otherwise similar in their characteristics and medical treatment.[22]

[22] One might be concerned that workers who are covered by Workers' Compensation insurance or claim medical benefits could change in response to the increase in maximum allowed reimbursement rates. This is unlikely for the following reasons. First, TDI regulates premiums of Workers' Compensation insurance and the major inputs for premiums is industry-specific risks and employer-specific past claiming history.

One might worry about the characteristics of workers who claim workers compensation medical benefits are affected by the changes in payment for medical services. On-the-job illnesses and injuries, which probably resulted from the nature of work and random accidents, are likely to be orthogonal to reimbursement for medical services. It unlikely that workers would change their behaviors of claiming workers compensation because of reimbursement received by physicians. Nevertheless, I check on the composition of employees entering workers compensation in table 1.5.[23] In the top panel of table 1.5, I aggregate data to the year-month level using the date of first claim for workers, and regress a linear trend, an indicator for after March 1, 2008, and the interaction term on outcome variable, including the total number of workers, the log total number of workers, and the median age of workers. In the bottom panel of table 1.5, data is aggregated to the year-month-county level and run a similar regression with county fixed effects. Both set of results show that the outcomes variables do not have different trend for post- policy time periods.

In addition, in figure A.1 in the appendix, I show the fraction of place of service (office, emergency department, inpatient, or outpatient) for patients' first visits in figure

The increase in payment to physicians are unlikely to enter into the calculations. Second, TDI updates premiums every year with a lag of at least three years to reflect the past costs of income benefits and medical benefits. If medical costs increased as a result of this policy change, it is not immediately reflected in Workers' Compensation insurance premiums. Third, medical benefits are fully covered under Workers' Compensation for work-related injuries. Workers covered by Workers' Compensation experience no change in price for claiming medical benefits.

[23] For each patient, I first identify the date of his or her earliest claim. Since data available starts only from January 1, 2005, I excluded workers whose earliest claims are within the range of January 1, 2006 to June 31, 2005 to make sure the earliest medical claims we observe are likely to be the first medical claims made by workers. I excluded workers whose earliest medical claims are within the range of July 1, 2012 to December 31, 2012, due to the possibility of updates in claim-level data afterwards.

A.1 (a) and the distribution of the main diagnosis for patients in figure A.1 (b) over time. It shows that the distribution of place of services and main diagnosis are relatively stable over time, indicating patients' medical conditions or choices of place for first visits do not changing over time.

Another way to check if the identification assumption holds is by examining the pre-policy year fixed-effects in the estimation results. As shown in section 1.5, all of the estimated pre-policy year fixed effects are insignificant, suggesting that there is no other confounding factors or trends.

1.4.3 First-Stage Effects

I first show the first-stage effect of the policy change on the average payment of surgical services per patient. I estimate the specification in equation 1.3 using the average costs of surgical services per patient previously defined as the outcome variable. Figure 1.1 shows that it takes a year for the average payment to respond and averaging the increase in the last three years, the average payment per patient increased by 12%. It took about a year for the increase in payment to reach 8%, and the change persists at that level until 2012. Since insurers typically negotiate rates with providers on an annual basis and might need some time to adjust, the gradual change in average payment is not surprising.[24]

[24] The actual increase in payment is smaller than the policy change in maximum allowed reimbursement rates. This means that the administrative increase in maximum allowed reimbursement rates for medical care is not fully transferred to providers. This partial transfer can be due to a few reasons. First, in healthcare networks within the Texas Workers' Compensation system or other agreements, insurers could pay lower than the maximum allowed amount. The maximum reimbursement amount regulated by TDI is only binding if there are no contracts or agreements between insurers and physicians. In healthcare networks or other agreements, insurers could negotiate for lower reimbursement rates and do not necessarily have to pass on the increase in maximum allowed reimbursement rates fully to providers. Second, it is possible that some

1.5 Estimation Results

This section presents the estimation results. To explore possible substitution between locations of care, I start by analyzing the changes in total RUVs for surgical services in a hospital setting and in an office setting. I then examine the possible spillover effects on nonsurgical services and provide evidence of complementariness between surgical and nonsurgical services. Additionally, I explore heterogeneity by looking at different types of services and elective services.

1.5.1 Baseline Estimates

To understand the effects of payment changes on the composition of medical service across locations of care, I examine the total RVUs for surgical services in a hospital setting and in an office setting per patient.[25] I estimate the specification in equation 1.3 and look at the total RVUs for surgical services in a hospital setting and in an office setting per patient.

For the total RVUs of surgical service per patient, figure 1.4 shows a 2% increase in the total RVUs of surgical services in a hospital setting. However, this increase is fully offset by the reduction in the total RVUs of surgical service in an office setting. As a result, the total RVUs of surgical services did not change. I also find similar results for

services are bundled together for payments. On average, the reimbursement paid for surgical services in facility may not fully reflect the change in policy. Third, rejections or disputes of claims could reduce the actual amount providers receive on average.

[25] As shown in figure A.2, about 77% of treatment are completed within three months. The distribution of duration of treatment has a long right tail, with roughly 10% of workers having a duration longer than 10 months. Based on the distribution for duration of treatment, to minimize the problem with truncation on duration of treatment, I will look at outcomes at work level within three months of treatment in the following sections. This allows us to analyze outcomes for workers in a comparable way without losing too much data.

the extensive margin. Figure 1.3 shows that there is a 1 percentage point increase in the probability of having any surgical services in facility settings, while the probability of having any surgical services stays unchanged. This indicates that the location of surgical services is highly responsive to the payment variations between hospital and office settings.

As a robustness check, I explore the substitution between locations of care further using within-service comparison and controlling for service fixed effects. Focusing on the set of surgical services that could potentially be performed in both hospital and office settings, figure 1.6 presents estimates from equation 1.4 using the log of the total number of surgical services per patient as the outcome variable. Before 2008, the estimates are insignificant and close to zero, indicating an absence of differential trends for surgical services in facility and nonfacility settings. The estimated coefficient of year 2008 is small, possibly because the year 2008 is partially affected by the policy change. The increase in relative quantity of surgical services in facility versus nonfacility increased by roughly 14% in 2009. For the next three years (from 2010 to 2012), the effect is much larger and is about 35%.

I also estimate an alternative specification using a simple $POST$ indicator to show the average effect for post-policy period. Table 1.8 shows that on average, the total number of surgical services increases in facility settings by 23.1% compared to that in nonfacility settings, while the relative average payment increased by 15%. Alternatively, if we focus on the last three years and take these estimates as long-run effects, from table 1.7 we have a larger effect of 35.5%.[26]

[26] If we take into account the estimated changes in relative payment for surgical services, the implied elasticity is about 2.07 (=35.5%/17.1%). As the total RVUs of surgical services per patient did not change

In addition, I find that the substitution between locations of care is present across the spectrum of surgical services, and it is not driven solely by the medical services initially with a low fraction performed in a hospital settings. I show the share of surgical services performed in facility settings over time in figure 1.7 (a). The share in facility is stable at the level of 47.5% before 2008. Then we observe an increase in the share in facility in 2008 and 2009, and an almost flat level of 56% from 2010 to 2012. This pattern is consistent with the estimated effects shown previously. Then I group surgical services based on the fraction performed in facility before 2008 into four categories using quartiles, as a measure of "facility intensity". Quartile 1 (Q1) includes the services with the lowest fraction in facility, while quartile 4 (Q4) has the highest fraction in facility. Figure 1.7 (b) shows the share in facility over time for each category. For all four categories, the share in facility has increased after the policy change for surgical services. This further confirms that the increase in surgical services in facility holds for medical procedures with different levels of "facility intensity".

1.5.2 Nonsurgical Services

Although nonsurgical services are not directly affected by the payment change, it is possible to observe changes in the quantity and composition of nonsurgical services, as nonsurgical services are likely to be complements to surgical services in the provision of medical care. For example, additional office visits are likely to be necessary when surgical services are provided. To examine potential spillover effects on nonsurgical services, I estimate the specification in equation 1.3 and look at the total RVUs for nonsurgical services

over time, we can interpret this elasticity as the elasticity of substitution between hospital and office settings.

in a hospital setting and in an office setting per patient.

Figure 1.3 shows that the RVUs of nonsurgical services increased by about 4%, and the increase mostly comes from the increase in the total RVUs of nonsurgical services in a hospital setting. Combined with the increase in the total RVUs of surgical services in a hospital setting, the results suggest that nonsurgical services are likely to be complements to surgical services.

The most possible reason for the complementarity between surgical services and nonsurgical services is bundled treatment. Patients might need to undergo many nonsurgical services for diagnostic or preparatory purposes before having a surgery. For example, for medical claims with at least one surgical service in a facility submitted in 2007, on average 28.32% of medical services are nonsurgical services.

I explore this possibility further by providing additional evidence supporting this argument. First, I take the nonsurgical services for patients who had at least one surgical service within two weeks, and show the change in total number of services for this subsample of nonsurgical services in figure 1.10 (a). The intuition here is to focus on nonsurgical services performed on the patients with possibly related surgical services, which are affected by the change in reimbursement rate. The estimated effect on this subsample is very similar to that from the overall sample.

Second, I restrict the sample to nonsurgical services which are typically performed within a short period of time of some surgical services. Using data before 2008, I first calculate the median of the number of days between the date of service of each nonsurgical service and the date when the closest surgical service performed. If the number of days apart is small for a certain nonsurgical service, then this nonsurgical service is likely to be related to some surgical services. Among all nonsurgical services, the median is roughly 20 days. So I estimate the same specification in equation 1.4 using a subsample of non-surgical services which are typically performed within 20 days of surgical services, with estimates plotted in figure 1.10 (b). Again, the estimated effect on this subsample is very similar to that from the overall sample, with possibly larger magnitudes for estimates in post-policy period.

1.5.3 Heterogeneity

Medical services vary in many dimensions, such as cost, risk, and intensity. In this section, I explore the heterogeneity of the estimated effects among surgical and nonsurgical services.

First, I group surgical and nonsurgical services based on the types using the American Medical Association (AMA) service categories. Table 1.9 shows that the changes in relative quantity is significant across all types of surgical services. The estimated effect is 26% for integumentary system services, 17% for musculoskeletal surgeries, and 44% for nervous system services.[27] For nonsurgical services, table 1.10 shows that the estimated increase in nonsurgical services in facility settings versus nonfacility settings is driven mostly by evaluation and management (E&M), anesthesia and radiology, which are the types of services one would expect to be performed along with surgical services. The estimated effects on pathology&lab, medicine, and device and equipment (D&E) are

[27] The first-stage effects on actual payment to providers vary by type of procedures as well, with larger changes for musculoskeletal surgery and nervous system services. Taking into account the first-stage estimates, the implied elasticity is larger for integumentary system and nervous system services.

insignificant.

Second, I also explore whether the response is more pronounced for elective surgical services. It is possible that physicians could change the options of medical treatment more easily for non-urgent and discretionary medical care. Figure 1.8 shows the effect on quantity for surgical services that are deferrable and non-deferrable medical services, respectively.[28] Deferrable medical service could be considered as relatively more discretionary. The estimates for deferrable services are close to the baseline results with slightly larger magnitude from 2010 to 2012, and small and nonsignificant for non-deferrable medical services.

Third, since the costs of healthcare vary substantially by geographic areas (Fisher et al., 2009), to explore possible differential effects across areas, I conduct the same analysis following equation 1.4 by hospital referral regions (HRR) in Texas - Houston, Fort Worth, San Antonio, Dallas, and Austin. As shown in table 1.11, the results are roughly similar to baseline estimates. The estimates are slightly larger for Houston and Dallas, which are both metropolitan areas with large manufacturing sectors, such as communications equipment, and oil and gas extraction (Assanie et al., 2007).

1.5.4 Discussion

Taken all together, patients received more care after 2008 when the reimbursement rates increased for surgical services in facility. Figure 1.2 shows the total RVUs of services increases by roughly 4.5%, averaging the estimates for the last three years. The increase

[28] See appendix A.1 for the definition of deferrable and non-deferrable medical services.

in total RVUs mostly comes from the increase in nonsurgical services.[29] With a 6% first-stage effect on the total costs per patient, the implied supplied elasticity is about 0.75. This small positive price elasticity of supply of medical care supports the upward-sloping supply curve.

For cost-benefit analysis of medical payment changes, the findings in this paper highlight the importance to consider possible substitution between locations of care and spillover effects for the impact on total medical spending. For the policy change studied in this paper, taking the first-stage increase in the average cost per patient, total costs per patient will increase by 6%, assuming there is no change in the provision of medical services by physicians. Adding the estimated effects on the total quantity of medical service per patient, this would translate to a 10.5% increase in average cost per patient. If we further include the additional payments to hospitals or other healthcare facilities due to the increase in medical services in a facility setting, the increase in medical spending would be even higher. Failing to consider the changes in total quantity and composition of care would lead to underestimation of the increase in medical spending.[30]

[29] The effects on the total quantity of medical services lags one year behind the effects on payment change. One possible reason is that physicians typically discuss medical treatment strategy and medical fee schedules annually. It is possible that physicians are not immediately fully aware of the payment changes and do not change their treatment choices at the same time. Additionally, it might be easier to change medical treatment and maximum profits for new patients, compared to existing patients.

[30] The analysis in this paper does not incorporate potential benefits to workers, such as higher quality of care and more effective medical treatment, when medical payments to physicians increase. It is possible that the increase in payment for surgical services in facility settings increased the duration of treatment, which in turn increased the days away from work, simply due to the fact that workers received more medical treatment or need additional time for physical therapy. On the other hand, if better medical services are provided for treating injuries, it could help shorten the course of treatment and days away from work. Unfortunately, with limited data availability, we could not directly evaluate the health outcomes for workers, such as physical functions post-injury and days away from work. The increase in follow-up visits and referrals to specialists indicates that access to healthcare for injured workers could have improved. Using the tabulated data on

The strong substitution documented in this paper also confirms the recent concerns on the differential payments across locations settings (MedPAC, 2013). If payment variations across location settings induce services to migrate from physicians' offices to higher paid hospital settings, hospitals could have incentives to acquire private practices and harvest higher payment from insures or government for the same medical services.[31] In the case of Medicare and private health insurance, the differential charges across settings could also impact cost-sharing for the insured patients.

1.6 Conclusion

This paper presents evidence on the impact of financial incentives on the quantity and composition of medical care provided by physicians. Using a sharp increase in the maximum allowed reimbursement rates for surgical services performed in a hospital setting for Texas Workers' Compensation medical claims, I document evidence of strong substitution in the location of care. I find that the 2% increase in surgical services provided in a hospital setting in response to this reform is fully offset by reduced utilization in an office setting. I also find that non-surgical services performed in a hospital increased in response to the reform, suggesting surgical and nonsurgical services are complements with

Nonfatal Occupational Injury and Illness Data for Texas from Bureau of Labor Statistics (BLS), for the time period studied in this paper, the median days away from work remains constant for minor injuries, such as sprains/strains, bruises/contusions, and cut/lacerations. However, for multiple traumatic injuries, the median days away from work decreased from an average of 15 days before policy change to 11 days afterwards. It is possible that with more medical services, workers with severe and complicated injuries recover more quickly.

[31] According to the American Hospital Association annual survey of hospitals, the number of physicians and dentists employed by hospital was relatively constant between 1998 to 2003 but grew by 55% from 2003 to 2011.

respect to physician financial incentives. Overall, my results also highlight the importance of accounting for the complements and substitutes of the category of care for which the payment changed for evaluation of medical payment reform.

The findings of this paper are directly relevant for the regulations on the reimbursement rates in Workers' Compensation system. Many states had explored or are currently considering changes in reimbursement system to design payments better, and fee schedules are the most widely used tools to regulate Workers' Compensation medical payments.[32] The findings should also be of interest to policymakers in other contexts, where there are changes in medical payment for a subset of medical services. For example, the Affordable Care Act increased medicaid payments to primary care physicians in 2013 and 2014. More broadly, my results suggest that the location of care is responsive to financial incentives, and optimal payment policy should account for substitution along this margin.

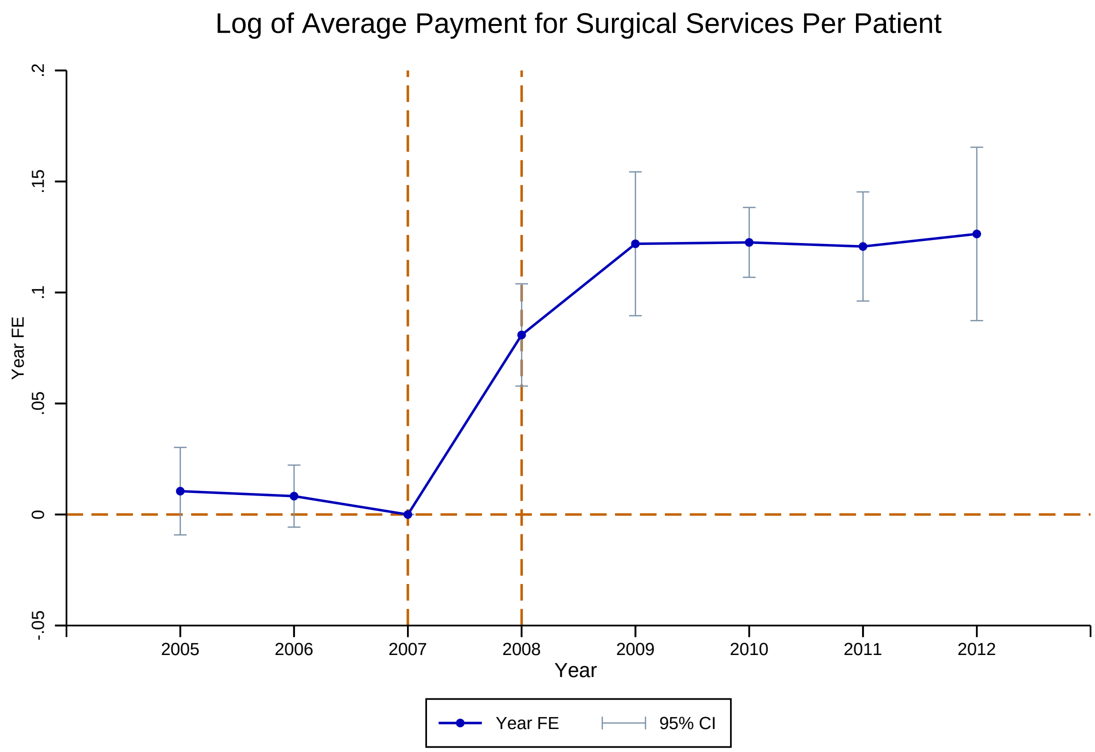
A natural step for future research is to explore further whether the differential financial incentives across locations impacts other outcomes, such as hospital employment of physicians, coordination of care across locations, and health outcomes for patients. It would also be interesting to analyze this research question for different payers, especially in the setting of Medicare and Medicaid, which are important sources of revenue for physicians and hospitals.

[32] For example, California enacted SB 863 in 2012, which required the Division of Workers' Compensation to transition the Official Medical Fee Schedule for physician services to a Medicare RBRVS system over four years. At the end of the four years, the reimbursement rate will be 120% of 2012 Medicare rates. California is currently exploring reforms for home health and ambulatory surgical services in workers' compensation as well (Wynn and Boustead, 2015; Wynn et al., 2014)

1.7 Figures and Tables

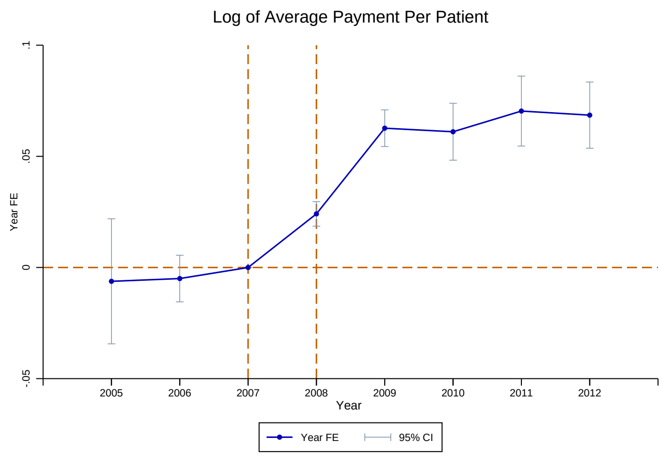
1.7.1 Figures

Figure 1.1

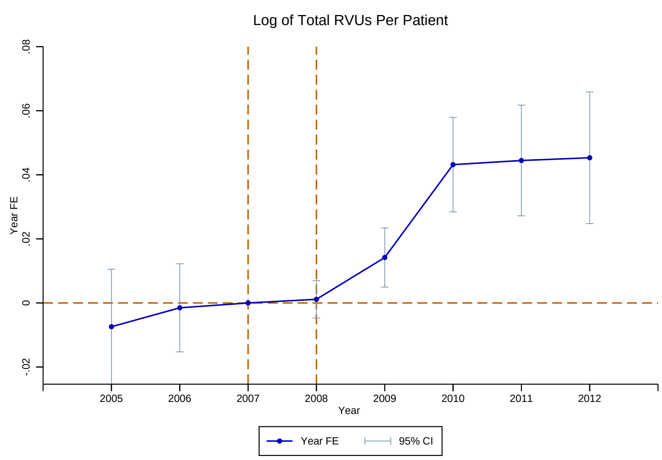


Notes: This figure plots the estimates of β_t from equation 1.3. Data is aggregated to the patient level from Texas Workers' Compensation medical claims data from 2005 to 2012. Year is based on the date of a worker's first claim. To ensure the accurate coding of date of first claims, employees with first claims from January 1, 2005 to March 31, 2005 are excluded. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the county level based on employees' places of residence. Outcome is the log of average payment per patient, holding quantity and composition of RVUs fixed over time.

Figure 1.2



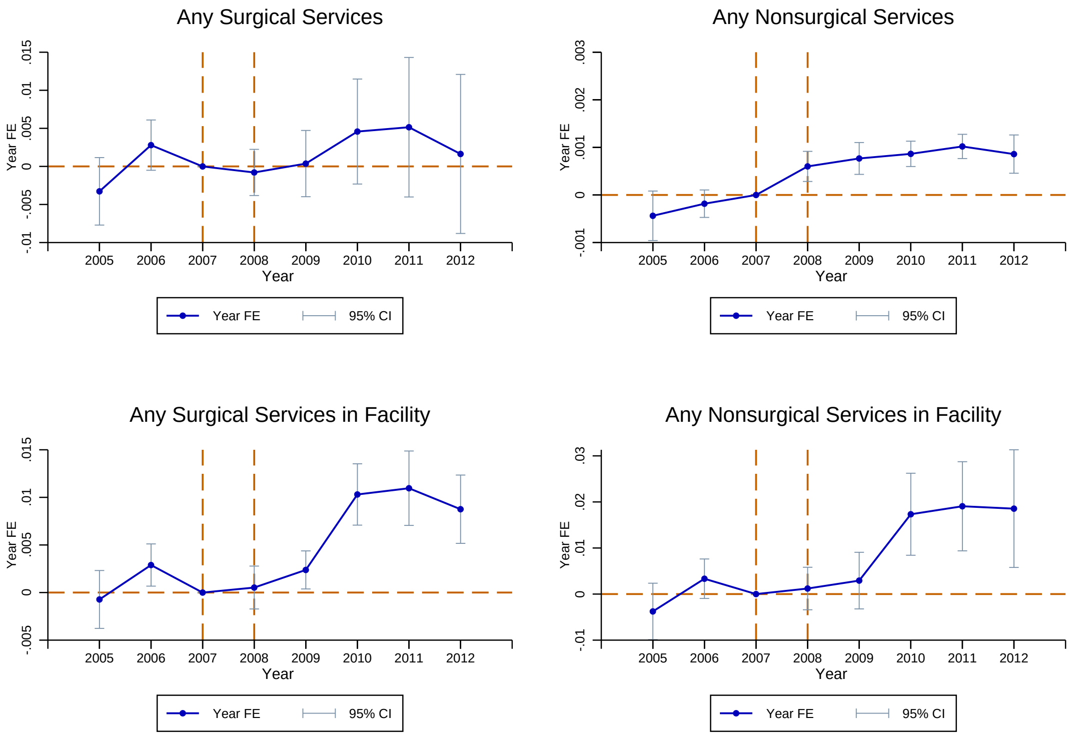
(a)



(b)

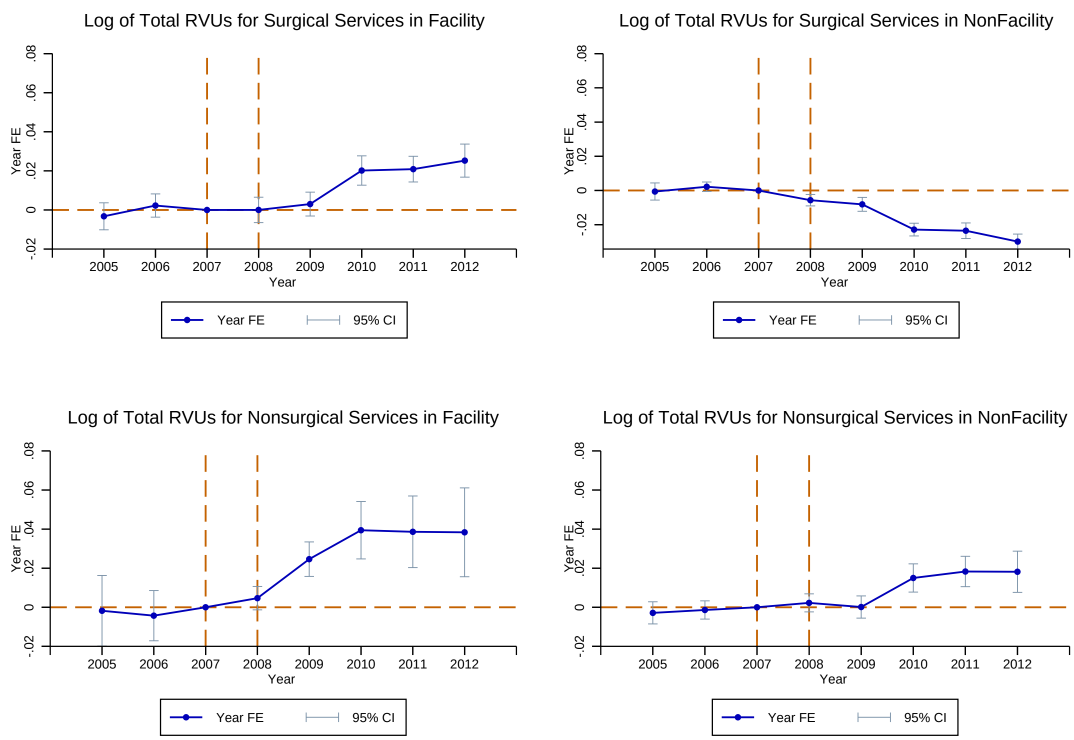
Notes: This figure plots the estimates of β_t from equation 1.3. Data is aggregated to the patient level from Texas Workers' Compensation medical claims data from 2005 to 2012. Year is based on the date of a worker's first claim. To ensure the accurate coding of date of first claims, employees with first claims from January 1, 2005 to March 31, 2005 are excluded. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at county level based on employees' places of residence.

Figure 1.3



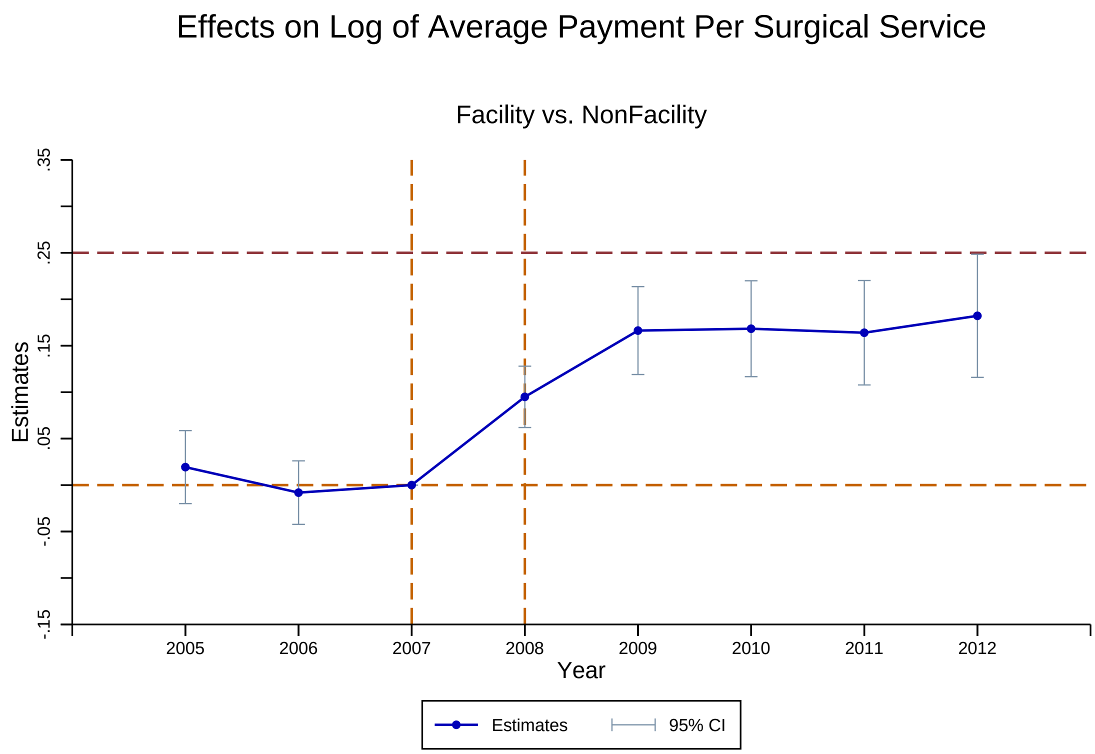
Notes: This figure plots the estimates of β_t from equation 1.3. Data is aggregated to the patient level from Texas Workers' Compensation medical claims data from 2005 to 2012. Year is based on the date of a worker's first claim. To ensure the accurate coding of date of first claims, employees with first claims from January 1, 2005 to March 31, 2005 are excluded. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at county level based on employees' place of residence. This set of figures shows the changes in outcomes for each subfigure at the worker level.

Figure 1.4



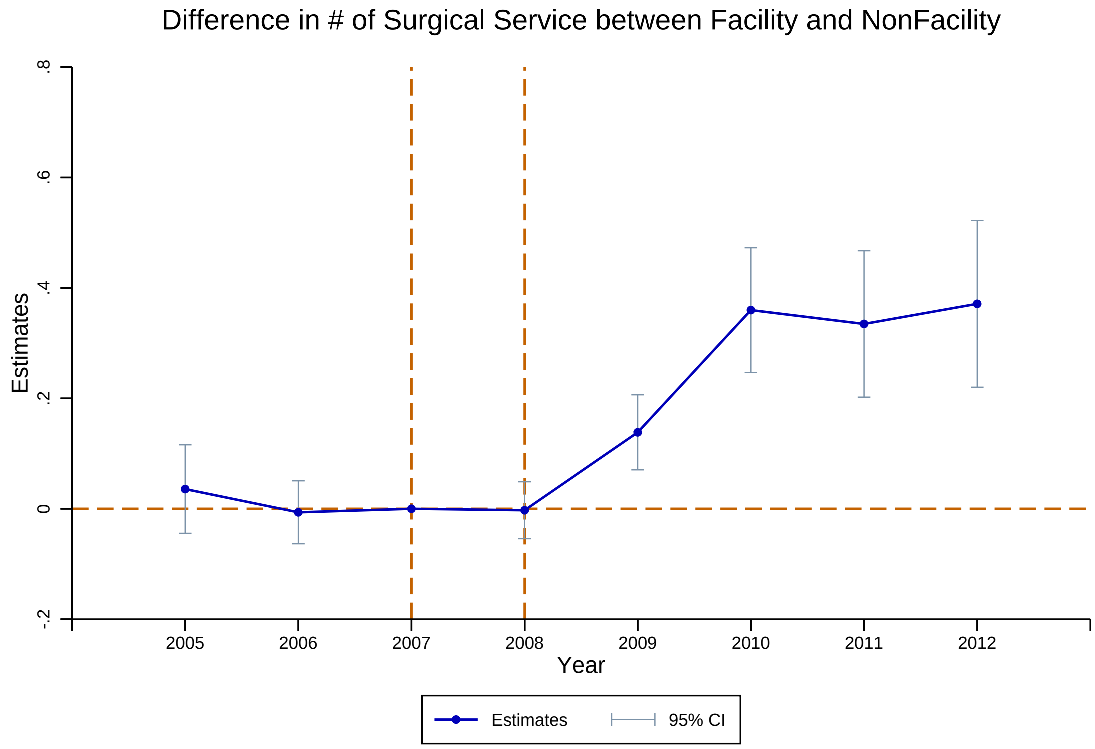
Notes: This figure plots the estimates of β_t from equation 1.3. Data is aggregated to the patient level from Texas Workers' Compensation medical claims data from 2005 to 2012. Year is based on the date of a worker's first claim. To ensure the accurate coding of date of first claims, employees with first claims from January 1, 2005 to March 31, 2005 are excluded. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at county level based on employees' places of residence. This set of figures shows that changes in outcomes for each subfigure at worker level.

Figure 1.5



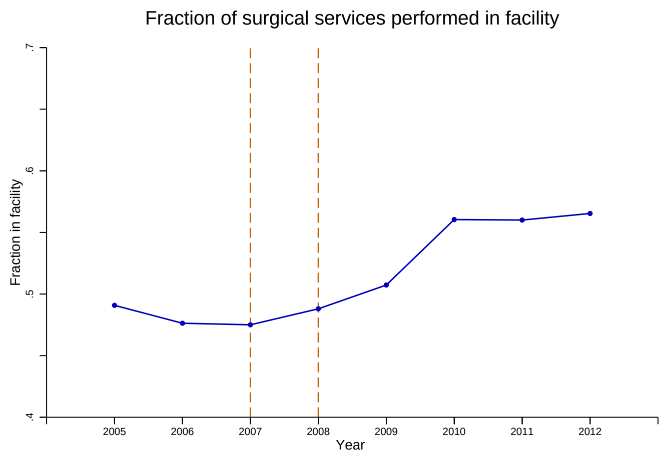
Notes: This figure plots the estimates of β_t from equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the average payment for surgical services (in log). The estimates show the differences over time in average payment for surgical services performed in facility, compared to surgical services performed in nonfacility settings.

Figure 1.6

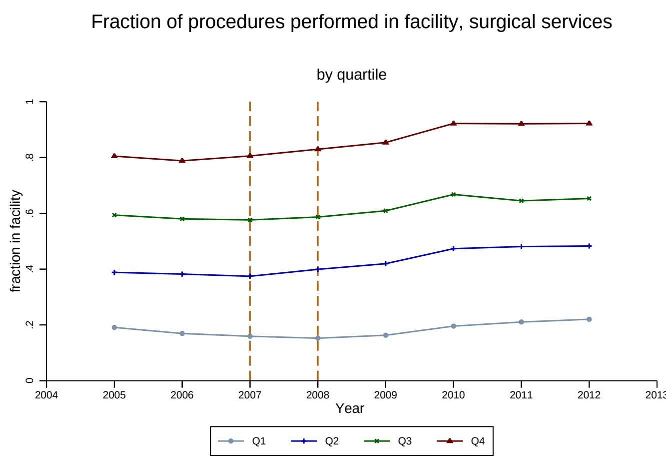


Notes: This figure plots the estimates of β_t from equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the total number of surgical services (in log). The estimates show the differences over time in total number of procedures between surgical services performed in facility and those in nonfacility settings.

Figure 1.7



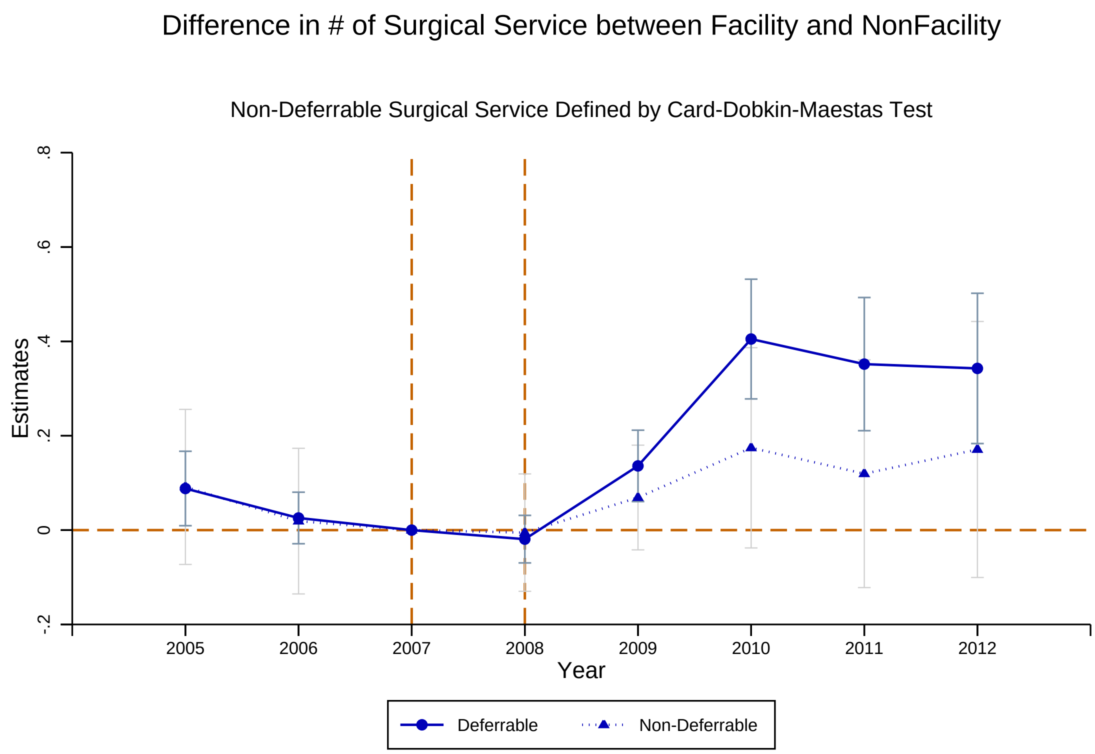
(a)



(b)

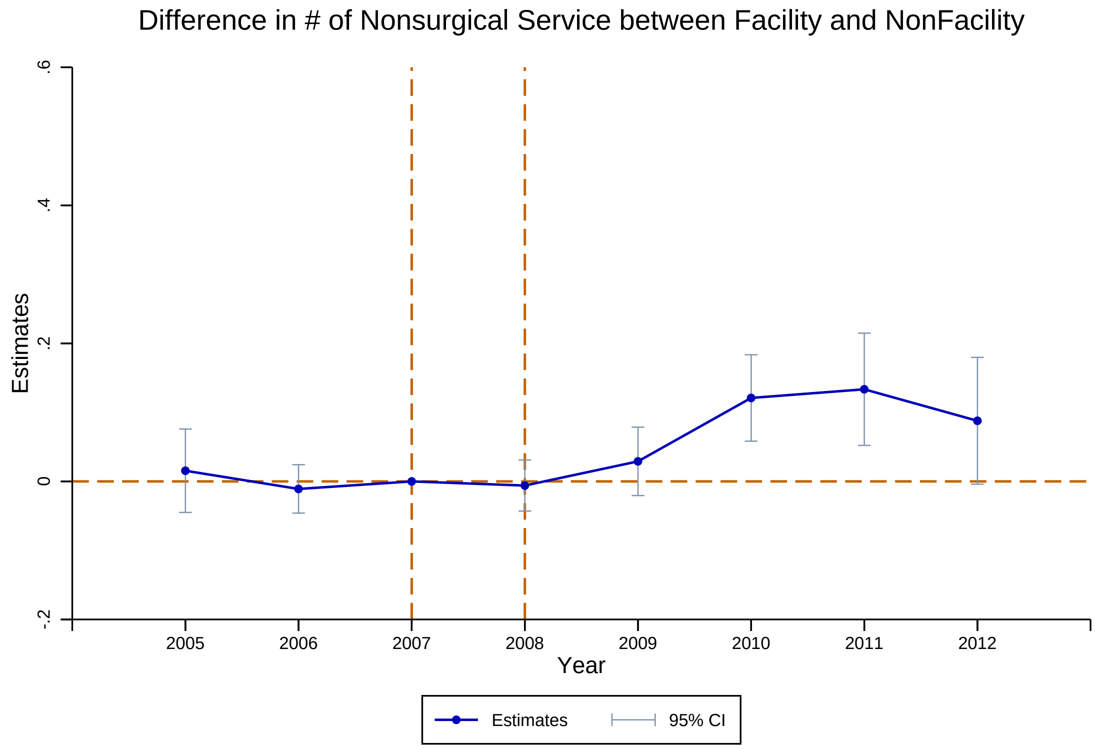
Notes: Figure (a) shows the share of procedures performed in a facility over time for surgical services. Figure (b) shows the share of procedures performed in facility over time, by quartile of share in facility. Quartile is defined using the share of procedures in facility in 2007: Q1 - 0 to 0.25, Q2 - 0.25 to 0.459; Q3 - 0.459 to 0.683; Q4 - 0.683 to 1. Higher quartile indicates that the surgical services are more like to be done in facility (more "facility intensive").

Figure 1.8



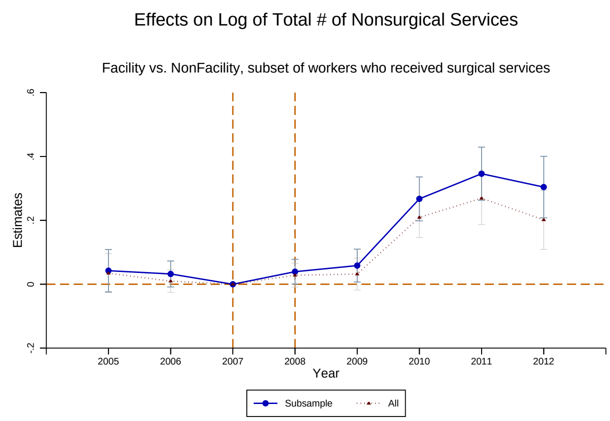
Notes: Note: This figure plots estimates of β_t from equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the total number of surgical services (in log) for a subsample of elective procedures. Definition of elective procedures is from a t-test of equal likelihood of weekday and weekend visits following Card, Dobkin, and Maestas (2009). Elective surgical services are mostly major cardiovascular or orthopedic procedures, ambulatory procedures, minor skin or musculoskeletal procedures, and endoscopy, imaging and routine venipuncture.

Figure 1.9

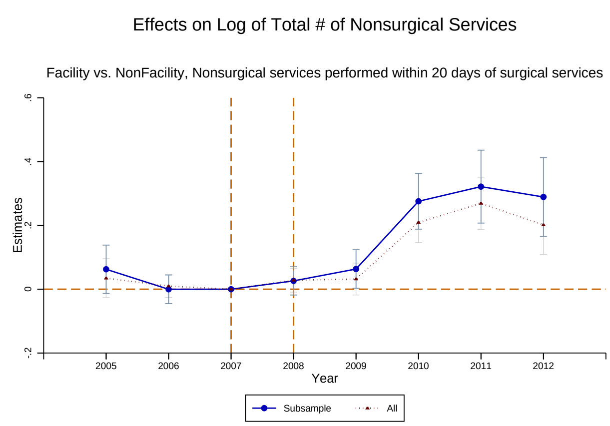


Notes: This figure plots the estimates of β_t from equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the total number of nonsurgical services (in log). The estimates show the differences over time in total number of procedures between nonsurgical services performed in facility and those in nonfacility settings.

Figure 1.10



(a)



(b)

Notes: This figure plots the estimates of β_t from equation 1.4 using subsamples of nonsurgical services defined below. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the total number of nonsurgical services (in log). The estimates show the differences over time in total number of procedures between nonsurgical services performed in facility and those in nonfacility settings. This set of figures explore the complementariness between surgical and nonsurgical services. Figure (a) shows the change in total number of services for nonsurgical services with certain surgical services during course of treatment for the same patients. Figure (b) shows the change in total number of services for nonsurgical services that are performed within 20 days of certain surgical services. See text in section 1.5.2 for more details.

1.7.2 Tables

Table 1.1: Share of Medical Claims by Location

Place of Services	**% of Medical Claims**
Facility	
Outpatient Hospital	30.91%
Inpatient Hospital	33.10%
Ambulatory Surgical Center (ASC)	18.30%
Emergency Room-Hospital	12.55%
Inpatient Rehabilitation Facility	0.90%
Nonfacility	
Office	52.20%
Home or Private Residence of Patient	19.82%
Health Clinic	10.23%
Independent Laboratory	5.85%
Urgent Care Facility	4.77%

Table 1.2: Conversion Factors

Year	Conversion Factor	Conversion Factor for Surgical Services in Facility
2005	49.45	
2006	50.83	
2007	52.20	
2008	**52.83**	**66.32**
2009	53.68	67.38
2010	54.32	68.19
2011	54.54	68.47
2012	54.86	68.88

Note: This table shows the conversion factors (CF) for professional services for Texas Workers Compensation medical claims. Before 2008, one conversion factor is applied to all type of services. Starting from March 1, 2008, a separate conversion factor, which is 25% higher than the standard level, is applied to surgical services performed in facility settings.

Table 1.3: Example of Medical Services

HCPCS	Description	Avg Payment ($)	% in Facility
Most Common Surgical Services			
20610	Arthrocentesis, aspiration and/or injection, major joint	35.39	5.03%
12001	Simple repair of superficial wounds of scalp, neck, etc	83.57	42.99%
64483	Injection(s), anesthetic agent and/or steroid, epidural	277.95	62.89%
62311	Injection(s), of diagnostic or therapeutic substance(s)	233.46	54.99%
29881	Arthroscopy, knee, surgical; with meniscectomy	564.05	84.63%
Most Common NonSurgical Services			
99213	Outpatient visit for evaluation and management	44.24	1.25%
97140	Manual therapy techniques (mobilization/manipulation)	17.58	0.28%
G0283	Electrical stimulation, to one or more areas	9.09	0.19%
72100	Radiologic examination, spine, lumbosacral	10.07	18.52%
85025	Blood count; Hgb, Hct, RBC, WBC and platelet count	10.68	51.97%

Table 1.4: Descriptive Statistics

	Mean	S.E.
Avg Number of Bills (each year)	2,898,938	176872.90
Avg Amount Paid per Bill ($)	231.12	10.81
Avg Amount Charged per Bill ($)	530.39	36.86
Avg Number of Workers (each year)	163,431	
Avg Duration of Injury (in days)	123.70	255.97
Median Duration of Injury (in days)	26	
Avg Costs Paid per Injury ($)	2779.67	9832.54
Avg RVUs per Injury	26.14	63.69
At Bill Line Level –		
% Surgical Services	4.09%	
% In Facility	57.80%	
% In Non-Facility	42.20%	
% Nonsurgical Services	95.91%	
% In Facility	6.93%	
% In Non-Facility	93.07%	

Note: This table shows the descriptive statistics using Texas Workers' Compensation medical claims data from 2005 to 2012. For duration of injury, to minimize the possibility of truncation, employees with first claims in 2005 and 2012 are excluded, and employees with last claims later than June 30, 2012 are excluded as well. Statistics for the bottom panel is from bill line level data sets.

Table 1.5: Check on the Patients' Characteristics

Check on the Characteristics of Worker Comp Patients

	# of Workers	Log # of Workers	Median Age
Month Level			
POST	-35.695	-0.001	-0.040
	(108.878)	(0.056)	(0.470)
POST*Trend	-14.414	-0.001	0.020
	(34.769)	(0.002)	(0.015)
Trend	-33.371	-0.002	-0.004
	(31.313)	(0.002)	(0.014)
N	84	84	84
Mean of Dep. Var.	19550.651	9.875	41.091
	# of Workers	Log # of Workers	Median Age
*County*Month Level*			
POST	-0.411	-0.015	0.338
	(2.239)	(0.025)	(0.320)
POST*Trend	-0.062	-0.001	0.010
	(0.075)	(0.001)	(0.009)
Trend	-0.184*	-0.002***	-0.006
	(0.097)	(0.001)	(0.008)
N	12852	12852	12852
Mean of Dep. Var.	94.49	3.16	41.54

Note: This table shows the estimates of specification with a linear trend, post indicator for after March 1, 2008, and the interaction term. In the top panel, data is aggregated to the year-month level using the date of first claim for workers. And in the bottom panel, data is aggregate to the year-month-county level and run a similar regression with county fixed effects. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1.6: Effect on the Total Quantity of Medical Services

	Surgical Services	**Elective Surgical Services**	**NonSurgical Services**
	Log of Total Number of Services	Log of Total Number of Services	Log of Total Number of Services
Facility*Y2005	0.036	0.088**	0.015
	(0.041)	(0.040)	(0.031)
Facility*Y2006	-0.006	0.026	-0.011
	(0.029)	(0.028)	(0.018)
Facility*Y2008	-0.003	-0.019	-0.006
	(0.026)	(0.026)	(0.019)
Facility*Y2009	0.138***	0.136***	0.029
	(0.035)	(0.039)	(0.025)
Facility*Y2010	0.360***	0.405***	0.121***
	(0.058)	(0.065)	(0.032)
Facility*Y2011	0.335***	0.352***	0.133***
	(0.068)	(0.072)	(0.041)
Facility*Y2012	0.371***	0.343***	0.088*
	(0.077)	(0.081)	(0.047)
Year FE	X	X	X
Service FE	X	X	X
Facility FE	X	X	X
N	3464	3464	2096
Mean of Dep. Var.	4.78	5.24	5.05

Note: This table shows the estimates of interaction terms of β_t from equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. This table reports estimates for log of average payment and log of total number of procedures, separately for surgical and nonsurgical services. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table 1.7: Effect on the Total Quantity of Medical Services (Short-/Long-term)

	Surgical Services		**Nonsurgical Services**	
	Log of Average Payment	Log of Total Number of Services	Log of Average Payment	Log of Total Number of Services
Facility*Y2005	0.019	0.036	0.027	0.015
	(0.020)	(0.041)	(0.018)	(0.031)
Facility*Y2006	-0.008	-0.006	0.025	-0.011
	(0.017)	(0.029)	(0.016)	(0.018)
Facility*Y2008-2009	0.131***	0.068**	0.019	0.012
	(0.018)	(0.028)	(0.015)	(0.021)
Facility*Y2010-2012	0.171***	0.355***	0.030	0.114***
	(0.025)	(0.064)	(0.020)	(0.038)
Year FE	X	X	X	X
Service FE	X	X	X	X
Facility FE	X	X	X	X
N	3464	3464	9680	9680
Mean of Dep. Var.	5.49	5.41	3.57	6.22

Note: This table shows the estimates of interaction terms of $POST_t$ (an indicator for year at or after 2010) and $Facility_s$, using specifications similar to equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. This table reports estimates for log of average payment and log of total number of procedures, separately for surgical and nonsurgical services. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table 1.8: Effect on the Total Quantity of Medical Services (Post Period)

	Surgical Services		**NonSurgical Services**	
	Log of Average Payment	Log of Total Number of Services	Log of Average Payment	Log of Total Number of Services
Facility*Post	0.151***	0.231***	-0.021	0.72**
	(0.020)	(0.053)	(0.017)	(0.035)
Year FE	X	X	X	X
Service FE	X	X	X	X
Facility FE	X	X	X	X
N	3464	3464	9680	9680
Mean of Dep. Var	5.50	4.78	3.57	5.05

Note: This table shows the estimates of interaction terms of $POST_t$ (an indicator for year at or after 2008) and $Facility_s$, using specifications similar to equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. This table reports estimates for the log of average payment and log of total number of procedures, separately for surgical and nonsurgical services. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table 1.9: Effect on the Total Quantity of Surgical Services by Type

By AMA Service Categories			
		Surgical Services Log of Total # of Procedures	
	Integumentary System	Musculoskeletal Surgery	Nervous System
Facility*Post	0.262***	0.170**	0.442***
	(0.067)	(0.076)	(0.122)
Year FE	X	X	X
Service FE	X	X	X
Facility FE	X	X	X
N	616	1960	624
Mean of Dep. Var.	4.53	5.31	5.85
First-Stage Estimates	0.076**	0.162***	0.183***
	(0.032)	(0.025)	(0.061)

Note: This table shows the estimates of interaction terms of $POST_t$ (an indicator for year at or after 2008) and $Facility_s$, using specifications similar to equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. Sample is restricted to surgical services, and each column is a separate regression on a subgroup of surgical services, based on HCPCS codes classifications. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table 1.10: Effect on the Total Quantity of Non-Surgical Services by Type

By AMA Service Categories

	Non-Surgical Services Log of Total # of Services					
	Evaluation &Management	Anesthesia	Radiology	Pathology & Lab	Medicine	Device &Equipment
Facility*Post	0.585***	0.601***	0.117*	-0.081	-0.046	-0.024
	(0.122)	(0.091)	(0.061)	(0.094)	(0.121)	(0.088)
Year FE	X	X	X	X	X	X
Service FE	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X
N	560	472	1864	1824	1584	3376
Mean of Dep. Var.	6.58	5.09	5.43	5.15	5.50	4.32

Note: This table shows the estimates of interaction terms of $POST_t$ (an indicator for year at or after 2008) and $Facility_s$, using specifications similar to equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. Sample is restricted to surgical services, and each column is a separate regression on a subgroup of surgical services, based on HCPCS codes classifications. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table 1.11: Effect on the Total Quantity of Surgical Services by HRR

	Log of Number of Surgical Services				
	Houston	Dallas	Fort Worth	San Antonio	Austin
Facility*Y2005	0.036	-0.083	-0.052	-0.147	-0.102
	(0.028)	(0.054)	(0.081)	(0.111)	(0.086)
Facility*Y2006	0.009	-0.012	-0.033	-0.035	-0.023
	(0.026)	(0.049)	(0.062)	(0.066)	(0.061)
Facility*Y2008	0.126***	0.098*	0.043	-0.004	-0.136
	(0.032)	(0.051)	(0.057)	(0.061)	(0.083)
Facility*Y2009	0.233***	0.173***	0.198***	0.200*	0.100
	(0.042)	(0.053)	(0.068)	(0.103)	(0.109)
Facility*Y2010	0.201***	0.250***	0.147	0.245**	-0.046
	(0.041)	(0.059)	(0.090)	(0.116)	(0.124)
Facility*Y2011	0.166***	0.213***	0.198*	0.194	0.012
	(0.045)	(0.080)	(0.108)	(0.126)	(0.142)
Facility*Y2012	0.229***	0.235***	0.225*	0.179	0.113
	(0.054)	(0.081)	(0.114)	(0.156)	(0.153)
Year FE	X	X	X	X	X
Service FE	X	X	X	X	X
Facility FE	X	X	X	X	X
N	1600	1488	984	720	456
Mean of Dep. Var.	5.41	5.98	6.85	6.76	6.90

Note: This table shows the estimates of interaction terms of β_t from equation 1.4, separately for each hospital referral region (HRR) in Texas. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. This table reports estimates for log of average payment and log of total number of procedures, separately for surgical and nonsurgical services. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Chapter 2

Cash-on-Hand and Demand for Credit

2.1 Introduction

People often rely on finance services to smooth consumption and build assets to cope with economic shocks and protect themselves against financial risks. Although many households in the United States have substantial ability to borrow, for the individuals with insufficient or inferior credit history, access to credit can be limited and costly.[1]

Researchers have long been aware of the importance of financial products in consumption smoothing. A substantial group of population relies on borrowing in small dollar credit to cope with the income shocks over payday cycles. This type of credit is very costly: borrowers could pay about \$15 for a \$100 loan on a typical 14-day storefront payday loan, equivalent to an annual percentage rate of charge (APR) of 391%.[2] Despite these high interest rates, about 15 million Americans used at least one payday loan at some time, and payday lenders have more store locations in the United States than the popular fast-food chain restaurant McDonald's locations(Ackerman et al., 2012; Stegman, 2007; Karger,

[1] Subprime borrowers typically have below-average credit scores and are charged with higher interest rates for loans or credit cards. Subprime borrowers are often identified by having a FICO credit score below 640, and this threshold varies slightly by lender, across financial products, and over time.

[2] This is a convenient way to compare the cost of short-term credit to other financial services, such as credit card and auto loans. However, using APR to measure the cost of short-term credit might not be entirely accurate. Some might argue it is not reasonable to compound the charges of short-term credit over the period of a whole year.

2005).

The literature have explored extensively the importance of liquidity and its impact on various outcomes, such as education (Manoli and Turner, 2014), health (Gross and Tobacman, 2014), mortality (Evans and Moore, 2012), consumption (Gruber, 1997) and bankruptcy filings (Gross et al., 2014). Tax refunds or stimulus payment have been used widely as sources of variation in income. In this paper, I extend this line of research further by analyzing how tax rebates affect households' financial situation, by looking at the demand for the small dollar credit.

Borrowers in the small dollar credit market tend to have volatile income and unstable employment status. They could also be eligible for certain various kinds of public assistance programs. As I will show in later sections, most of the borrowers are also eligible for Earned Income Tax Credit (EITC) benefits, and it is likely that some of the borrowers are eligible for Temporary Assistance for Needy Families (TANF), Food Stamps, or have household members who receive unemployment benefits or social security payments. Understanding how borrowing patterns change in response to tax rebates from EITC would provide evidence on how the additional benefits from public programs help with households' financial situations.

Using unique loan-level data from a credit bureau that specializes in subprime lending, I utilize variation in EITC generosity across state borders to examine the impact of income shocks on the demand for credit. Combining with tax return data at the 5-digit ZIP code level, I focus on ZIP code areas that belong to the same commuting zone, which spans across state borders. I will show that residents in the same commuting zone share similar demographic and socioeconomic characteristics. The only significant difference in their income comes from the different generosity of state EITC benefits. Using the commuting zone that spans the border of Texas and New Mexico as an example, Texas does not offer any additional state EITC benefits, while New Mexico has an additional 10 % of federal EITC benefits. One might expect residents in New Mexico near the border would borrow less as a result of the additional state EITC benefits. I use this plausibly exogenous variation in EITC benefits to estimate the effect of tax rebates on the demand for small dollar credit. The estimates can be interpreted as local average treatment effect - the effect of having additional EITC benefits on borrowing for those who live in a state with higher state EITC top-up rates.

The empirical results show that borrowers are quite sensitive to income shocks. A \$100 increase in EITC benefits leads to a 8.3% reduction in the number of loan applications and a 6.6% reduction in the number of borrowers. This could translate into sizable reductions in loan volume and savings in financial charges. With \$100 additional EITC benefits, each borrower could save \$13 on interest charges alone. The estimates are robust to various specifications checks.

This paper contributes to the literature in a number of ways. First, this paper builds on a large literature that studies the effect of income shocks on consumption. Researchers often study the sensitivity of consumption to income, using variation from tax rebates or refunds (Bertrand and Morse, 2009; Gross and Tobacman, 2014), ending of mortgage or car loan payments (Coulibaly and Li, 2006), or minimum wage hikes (Aaronson et al., 2012). This paper adds to this line of literature by looking at the households' debt. Although consumption is central to testing the permanent income theory, it is also important to know how debt changes in response to income in order to obtain a complete picture of households' financial situations.[3] Second, this paper provides a causal estimate of the effect of tax rebates on the demand for small dollar credit. Third, the empirical results also provide evidence on the benefit of EITC for reducing financial costs among the eligible population. With an imperfect credit market and limited access to traditional financial products, the cost of borrowing could be substantially high. Borrowers could fail to pay the fees and interest and get trapped in vicious borrowing cycles. Income benefits from EITC and other public programs could help alleviate the financial burdens people face.

The results have several important implications on public policies and the credit market. First, with frictions in the credit market, public programs, such as EITC, have the additional benefit of reducing the use of costly credits and helping consumers smooth consumption. In the absence of a fully functioning credit market, government programs could act as insurance against adverse financial events. Second, the empirical results show that demand for small dollar credit is quite sensitive to income shocks. Consumers significantly reduce their use of costly credit when cheaper liquidity is available, indicating that EITC recipients might be liquidity constrained. Third, the analysis of this paper underlines the importance of accurate measures of income in the credit market. Most lenders in the sub-prime industry typically rely on self-reported income for underwriting, if there is any underwriting at all. An accurate measure of income is critical to evaluate borrowers' risk and to reduce the default rate for lenders.[4] Consumer advocates often argue that small dol-

[3] Income and debt could be imperfect substitutes. One might expect marginal propensity to consume (MPC) is different for income, compared to MPC for debt.

[4] Most subprime consumers have multiple jobs. They have incentives to report their income strategically to gain more access to credit and better loan terms. Common characteristics of subprime consumers include limited or inferior credit history, volatile income or employment history, and facing relatively high financial uncertainty.

lar loans are too costly and should only be restricted to people who have the ability to pay. Accurate income measures and elasticity of demand for credit to income shocks would also be a key factor, when lenders build underwriting models and identify the population with sufficient ability to pay.[5]

The paper unfolds as follows. Section 2.2 discusses the conceptual framework. Section 2.3 describes the institutional setting explored in this paper. Section 2.4 discusses the empirical strategy and identification assumptions. Section 2.5 describes the data. Section 2.6 shows the empirical estimates of elasticity of demand for credit to income shocks, placebo tests and robustness analysis. Finally, section 2.7 concludes the paper.

2.2 Literature Review

There is a large literature on the importance of liquidity and its impact on various outcomes, such as education (Manoli and Turner, 2014), health (Gross and Tobacman, 2014), mortality (Evans and Moore, 2012), consumption (Gruber, 1997) and bankruptcy filings (Gross et al., 2014). Tax refunds or stimulus payment have been used widely as a source of additional income. For example, Gross and Tobacman (2014) exploit the randomized timing of one-time payment from the 2008 Economic Stimulus Payments, and Shapiro and Slemrod (2003) use tax rebates in tax year 2001 as the exogenous variations in income. Researchers have used other variations in EITC benefits to study the impact of liquidity on outcomes such as education attainment. For example, Michelmore (2013)

[5] For example, CFPB is considering imposing regulations on rollover or renewal of payday loans at national level, based on borrowers' income or other characteristics (see proposal from CFPB). Pew institute has proposed a 5% loan-to-income ratio as the benchmark for underwriting (see details from the Pew institute).

use across-state and over time variations of EITC benefits to study the effects of income on education attainment. LaLumia (2013) use the timing of EITC payment to study the impact of EITC receipts on unemployment spells.

This paper adds to the literature by exploiting the cross-sectional differences in state EITC benefits in a new way. The variations in income resulting from EITC benefits are partly expected by eligible taxpayers and are not one-time payments. This supplements the existing research which use temporary income shocks for one-time stimulus payments.

Before analyzing the effects of additional EITC benefits on the demand for small dollar credits, we need to know how recipients typically use tax rebates or EITC refunds. Barrow and McGranahan (2000) find that EITC receipts help low-income families purchase big-ticket durable goods and smooth expenditure to some extent. Using the economic stimulus payments of 2008, Parker et al. (2013) find similar results of substantial consumption out of tax rebates. Agarwal et al. (2007) find that credit card borrowers receiving tax rebates had a large increase in credit card spending. Related to this paper's research question, Bertrand and Morse (2009) find a persistent decline in payday borrowing in the pay cycles that follow the receipt of the 2008 tax rebate. Based on the evidence in the existing literature, tax refunds are typically used for consumption, possibly the purchase of large items or durable goods, or to pay off debts. [6]

This paper expands the scope of outcomes in literature and looks at taxpayers' financial situation, focusing on the use of high-cost short-term payday loans. Short-term

[6] These papers also highlight the importance of liquidity, especially for low-income families. Related studies can also be found in sociology. For example, Sykes et al. (2015) offers detailed accounts of the use of tax refunds through in-depth interviews.

small dollar credit is typically not a substantial part of a household's financial portfolio. However, due to its high costs and short-term nature, use of these types of financial products could be viewed as an indicator of a deteriorating financial situation.

Another line of research related to this paper focuses on the consequences of payday loans. Researchers have been long interested in quantifying the impact of payday loans on consumers. Carrell and Zinman (2008) and Melzer (2011) both find that the use of high-cost payday loans has a negative impact on borrowers. Evaluating the effects of payday loans on consumers is beyond the scope of this paper. Based on the existing literature, we can interpret the reduction in the use of payday loans as an improvement of households' financial situation, which also indicates savings in fees and interest. I consider the reduced demand for small dollar credit as beneficial to consumers financially, since the interests and fees associated with this credit is avoided.

2.3 Background

2.3.1 Small Dollar Credit Industry

Small dollar credit offers short-term consumer loans of small amount, ranging from \$100 to \$1,000. The most common type of small dollar credit is payday loans. Other types of small dollar credit include installment loans, check cashing, rent-to-own, auto loans, title loans, lines of credit, etc.

Consumers' demand for small short-term consumer loans have long existed. The payday loan industry has grown dramatically since its inception in the early 1990s. Stegman (2007) estimated that payday loan volume expanded five times to almost \$50 billion from the late 1990s to the mid-2000s. According to Pew (2012), 12 million American households borrow on payday loans each year, and a borrower on average takes out eight loans of $375 each per year and spends $520 on interest. Payday loans are short-term loans for immediate cash, typically secured by a borrower's written check or authorization for automatic withdrawal from the borrower's bank account. Stephens Inc. estimates that payday loan volume was roughly $45 billion in loan volume and $9 billion in revenue in 2014, including both storefront and online lending. [7]

In a typical payday loan transaction, the customer (borrower) writes a check for the amount of the loan and finance charges. The creditor (lender) agrees to hold the check until the next payday, typically about two weeks, when the customer redeems the check with cash or the creditor deposits the check.[8] On average, a consumer typically incurs $15 in fees on a $100 payday loan. Typical annual percentage rates (APR) for payday loans range from 391% to 443%. They are called "payday loans" because they are marketed as a tool for borrowers to make it to the next paycheck. Other similar financial products in the small dollar industry are also tied to the date of the next paycheck, such as installments and line of credit.

Since the loan comes due on payday, borrowers expect to have money in their account to cover the check. Borrowers who do not have the funds to repay the loan and meet other expenses must make one of three choices: (1) extend or rollover the loan, (2) pay off the loan but borrow again from the payday lender immediately in a "back-to-

[7] Full report is available from CFSA.

[8] To get a loan, a borrower gives a payday lender a postdated check (e.g., dated on the borrower's next payday) and receives cash right away. The borrower will pay the full loan amount and fees on the next payday. The lender then holds the check until the borrower's next payday, which generally falls anywhere from less than a week to a month later.

back" transaction, or (3) default, and consequently incur bounced check fees by the payday lender and insufficient fund (NSF) fees by the borrower's bank while still owing the full amount of the original post-dated check.[9]

Payday loan customers face limited credit availability and have fewer alternatives than the average consumer. Nearly three-fourths of payday loan customers have been turned down by a creditor or not given as much credit as applied for. Payday loan customers were less likely than the general population to have a bank or retail credit card (Elliehausen and Lawrence, 2001).

2.3.2 Regulations

Consumer lending markets have been highly regulated, subject to usury laws and small loan laws that limit interest rates and principal amounts, among other terms and conditions. Among high credit-risk individuals, interest rate caps can be binding and lead to credit rationing. Payday loan credit is regulated by state and federal laws.[10] In addition, many payday loan companies voluntarily adhere to a set of industry standards promulgated by an industry trade association, the Community Financial Services Association of America (CFSA), as a form of self-regulation.

Payday loans are consumer loans and, therefore, are subject to the federal Truth in Lending Act (15 U.S.C. 1601 et seq.), which is implemented by the Federal Reserve Board. Truth in Lending requires a detailed set of disclosures of the price and other terms

[9] Lanning et al. (2014) document that the payday loans are often rolled over or followed by another loan within 14 days.

[10] See state-level regulations on payday loans at NCSL.

of consumer credit transactions. The key price disclosures are the annual percentage rate and the finance charge.[11] The Fair Debt Collection Practices Act (15 U.S.C.1692 et seq.) establishes debt collection standards for third-party collectors. The act prohibits harassment, false statements, and certain practices in collecting debts.

Thirty-two states have legislation or regulations explicitly authorizing payday loans. Typically, the state payday loan laws exempt payday loans from usury or interest rate ceilings, in exchange for establishing maximum fees and rollover limits. The state payday loan laws also require licensing and periodic examinations to ensure that the licensees are abiding by all applicable federal and state laws.[12] Eighteen states and the District of Columbia prohibit payday lending through strict interest rate ceilings, which make very small loan sizes unprofitable.[13]

State laws also regulate nonprice terms of payday loan transactions in several ways. Some laws limit the number of times an advance may be rolled over or refinanced. Eighteen states (e.g., Colorado, Florida and Kansas) do not permit a payday loan customer to

[11] The annual percentage rate is the periodic interest rate applied to outstanding balances multiplied by the number of periods in a year. The finance charge is the total dollar amount of all interest payments. Other disclosures for payday loan transactions include the amount of the loan (amount financed), the total of payments (for payday loans, the check amount), and the schedule of payments.

[12] Thirty-two states enacted safe harbor legislation for payday lenders and permit loans based on checks written from consumers' bank accounts at triple digit interest rates, or with no rate cap at all. These states include: Alabama, Alaska, California, Delaware, Florida, Hawaii, Idaho, Illinois, Indiana, Iowa, Kansas, Kentucky, Louisiana, Michigan, Minnesota, Mississippi, Missouri, Nebraska, Nevada, New Mexico, North Dakota, Oklahoma, Rhode Island, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Washington, Wisconsin, and Wyoming. See statutes from NCSL for details.

[13] In the online small dollar credit market, lenders can operate under two different legal models. They can choose to obtain state licenses and comply with state level regulations, or they can choose to locate and register their company at tribal areas or offshore locations and bypass any regulations. State licensed lenders make up the most part of the industry. In the baseline analysis, I focus on state-licensed lenders and provide results including offshore or tribal lenders as robustness checks.

retire an existing advance with a new advance. Five states (e.g., Idaho and Illinois) permit a current advance to be rolled over no more than three times. Many payday loan laws limit the size of payday loans.[14]

2.4 Empirical Strategy

2.4.1 Overview

To identify the causal effect of income on demand for credit, one has to isolate exogenous shocks in income. Analysis using cross-sectional or time-series data alone could be problematic and suffer from endogeneity problem. Indeed, using cross-sectional data, I observe a positive correlation between the number of EITC recipients and the number of borrowers in a subprime market. Figure B.1 shows borrowers of small dollar loans and EITC benefits received across counties, respectively. It is obvious that there are more borrowers and, at the same time, a higher amount of EITC benefits received in southwestern areas. This pattern is not surprising given that EITC recipients and borrowers could share common socioeconomic characteristics, such as education attaintment, income and economic shocks. It highlights the importance of using exogenous variations for identification.

To overcome the endogeneity problem, in this paper I exploit the different state

[14] Size limits frequently range between \$300 and \$500 per advance. Some states directly limit the size of the advance. Others limit the size of the check, which includes the amount of the advance plus the finance charge. Montana has a variation on size limits that restricts advances to the lesser of \$300 or 25% of the customer's net monthly income. Nevada limits the amount of the advance to one third of the customer's net monthly income. Many states also limit the aggregate amount of advances to a customer at a company, which is generally the same as the size of the maximum advance. The intent of these restrictions on nonprice terms is to force consumers to use payday loans for short-term needs and to keep the consumers from falling too far into debt.

EITC top-up rates for people living in the same commuting zone and close to state borders. Commuting zone is constructed to better delineate local economies and measure the local labor market.[15] People in the same commuting zone face the same labor market conditions and experience the same economic shocks. Arguably, the only difference is that households on one side of the state border could be eligible for additional EITC benefits, typically measured as a percentage of the federal EITC benefits.

I assume that variations in income due to different generosity of state EITC benefits are exogenous. Supporting evidence will be provided in later sections. Using American Community Survey (ACS) summary files, I will show that demographic and socioeconomic characteristics are not correlated with state EITC top-up rates. State level characteristics, such as unemployment benefits, receipt of food stamp benefits, minimum wage, and regulations in the small dollar credit market are not correlated with state EITC generosity either.

The estimates using the variations in EITC generosity across state borders could be interpreted as the local average treatment effect on the population living close to state borders where state EITC top-up rates vary.

2.4.2 Identification

The Earned Income Tax Credit (EITC) is a federal tax credit for low- and moderate-income working people. It encourages and rewards work as well as offsets federal payroll and income taxes. States can choose to offer additional benefits on top of federal EITC

[15] For more details on construction of commuting zones, see documentations from USDA.

benefits. Twenty-six states, including the District of Columbia, have established their own EITCs to supplement the federal credit.

In the 2012 tax year, about 26 million working families and individuals received the EITC benefits. The amount of EITC depends on a recipient's income, marital status, and number of children. In the 2014 tax year, working families with children that had an annual incomes below about $37,900 to $51,600 (depending on marital status and the number of dependent children) may have been eligible for the federal EITC. Also, working-poor people without children that have incomes below about $14,300 ($19,700 for a married couple) can receive a very small amount of EITC.[16]

State EITC top rate ranges from 5% to 33% of federal EITC benefits. The eligibility requirements of state EITC benefits are identical to federal EITC. People who file both state and federal tax returns would get both federal and state EITC benefits, if eligible. In particular, most people use paid services (for example, H&R Block), when filing tax returns. The paid tax preparation services have strong incentives to encourage people to take up and file for both federal and state EITC benefits, if eligible.

Although the state EITC top-up rates are constant over time in most states, the exact amount of the additional EITC benefits depends on a taxpayer's income and could be considered as random and exogenous income flows. This source of variation in income is different from those used in previous research. For example, tax rebates are temporary and one-time shocks. Though it is useful to study the short-term response to tax rebates, people facing more permanent and longer term income shocks could behave differently.

[16] For most updated information on eligibility and generosity of EITC, see details from IRS.

Also, estimates using income shocks from EITC could be applied to other public programs as well, such as unemployment insurance and Temporary Assistance for Needy Families (TANF).

As described above, in this paper I exploit the cross-state variations in state EITC top-up rates. Cross state variations alone are not enough to guarantee causal identification. Residents in different states could be different in many dimensions, such as income, labor market conditions, and economic shocks. To overcome this issue, I focus on commuting zones (CZs) that span more than one states. CZs are larger than counties and are approximately the size of 3-digit zip area (ZIP3): there are 709 CZs and about 913 ZIP3 areas in the United States. Unlike counties or zip code areas, the commuting zones were first developed by USDA Economic Research Service in the 1980s as a way to better delineate local economies. County boundaries are not always adequate confines for a local economy and often reflect political boundaries rather than an area's local economy. CZs are geographic units of analysis intended to more closely reflect the local economy where people live and work.[17]

2.4.3 Assumptions for Identification

The exogenous variation I use in EITC benefits arises from differences in state EITC top up rates that occur at state boundaries. For this identification strategy to be valid, within-CZ variation in EITC benefits only occurs at the state border - people living in the same commuting zone are otherwise identical. One can also think of the exogenous

[17] I use CZs updated in 2000 and a crosswalk between ZIP code areas and CZs to identify borrowers' location from loan-level data.

variations in state EITC benefits as an instrument for households' income. For an instrument to be valid, it has to be exogenous, that is, unrelated to other omitted factors that might also affect the outcome variable, and be correlated with the variable it instruments for (in this case, income levels).

Other factors of income shocks and borrowing behaviors could vary continuously over geography as well. If these determinants are correlated with the instrument, state EITC top-up rates, then the identification would not be valid. I address this concern by providing a thorough analysis to support the identification assumption.

2.4.4 Estimating Equations

Given the cross-border variation in state EITC top-up rates, one way to estimate the demand for credit is to run regressions of the number of loan applications on EITC benefits received in the sample of cross-border CZs. However, this approach suffers from an endogeneity problem, since the actual amount of benefits received depend on a tax filer's income, marital status, and number of dependents.

One approach is to use state EITC top-up rates as an instrument for actual benefits received. In absence of any fraud in claiming EITC, this should be a valid strategy. To facilitate the interpretation of the estimates in dollar terms, I follow the simulated instrument approach (Currie and Gruber, 1996). I construct a cross-state simulated instrument by calculating the eligible amount of EITC benefits using a constant, nationally representative sample for the US population. The simulated instrument isolates the variations from the state level policy, and eliminates confounding factors, such as the demographic and socioeconomic characteristics of residents across states.

For state s and year t, the instrument is given by

$$SimEITC_{st} = \frac{1}{I}\sum_{i\in I} \$EITC_{ist}(Filer\ Status_{ist}, Income_{ist}, Num\ of\ Dependents_{ist}) \tag{2.1}$$

Given the constructed simulated instrument, the first stage regression is given by the equation below. By construction, it should have a high value for R-squared and an estimate of ρ close to one.

$$AvgEITC_{zt} = \rho SimEITC_{st} + \gamma_c + \theta_t + \alpha X_{zt} + \xi_{zt} \tag{2.2}$$

where X_{zt} are local characteristics, γ_c are commuting zone fixed effects, θ_t are year fixed effects, and ξ_{zt} is the error term. $SimEITC_{st}$ is the simulated instrument constructed from above.

The reduced form is given by

$$Y_{zt} = \beta SimEITC_{st} + \delta_c + \zeta_t + \eta X_{zt} + \epsilon_{zt} \tag{2.3}$$

where X_{zt} are local characteristics, δ_c are commuting zone fixed effects, ζ_t are year fixed effects, and ϵ_{zt} is the error term. $SimEITC_{st}$ is the simulated instrument constructed from above.

To facilitate interpretation of the estimates, the following IV specification is estimated:

$$Y_{zt} = \phi AvgEITC_{st} + \kappa_c + \sigma_t + \tau X_{zt} + \nu_{zt} \tag{2.4}$$

where X_{zt} are local characteristics, κ_c are commuting zone fixed effects, σ_t are year fixed effects, and ν_{zt} is the error term. $AvgEITC_{st}$ is the actual amount of EITC benefits received and will be instrumented using $SimEITC_{st}$.

The key parameter of interest is ϕ, which can be interpreted as the effect of additional EITC benefits for people who are eligible and reside in states with generous EITC benefits on borrowing decision. Y_{zt} is some measure of demand, such as the total number of borrowers, the total number of loans, and the total dollar amount of loans, either from loan applications or funded loans. If Y_{zt} is measured as total dollar of loans funded, the coefficient can tell us the amount of loans in dollars that was replaced by $100 extra EITC benefits. To control for differences in characteristics across commuting zones, I include controls for income distribution, which is measured as the percentage of population with income in certain range from IRS data, and for size of population in X_{zt}.

2.5 Data

Data for this project comes from multiple sources. The primary source for tax return data at the 5-digit ZIP code level come from the IRS and Brookings Institution.[18] In tax return data, for each ZIP5 area, the total number of tax return filers, the total number/amount of refunds, the number of federal EITC recipients and the total amount of

[18] The Brookings Institution uses original aggregated level data from the IRS. The difference is that the Brookings Institution re-assigned residence to more accurate and consistent ZIP code areas and counties. Data from the Brookings Institution also includes some additional information on EITC-eligible tax filers.

federal EITC benefits received is available in the tax return data.

Since the tax return data only includes federal tax filings, I assume that people who file federal tax returns would also file state tax returns. This is a reasonable assumption for the following reasons. First, a substantial part of the population eligible for EITC use paid tax filing services, which would mostly likely assist taxpayers to file and claim any refunds both at the federal and state level. Second, people using electronic tax filing would file for both federal and state returns automatically.[19] Third, taxpayers would have strong incentives to file for both, if eligible for any public assistance.

The small dollar credit market, especially the online subprime lending market, has grown dramatically in the last decade. Data on this type of high-interest lending are typically proprietary and confidential. This paper takes advantage of a unique and new dataset from a major credit bureau specializing in the online subprime lending market, which has the most complete data coverage of United States, to my best knowledge. This data set includes demographic and credit history information for loan applicants and loan level characteristics from reporting lenders in this industry.

The loan level data includes both loan applications and funded loans from 2010 to 2014. In both applications and funded loan data, borrowers' characteristics, such as monthly income, date of next paycheck, pay frequency, data of birth and location of residence (5-digit ZIP code) are available. For a subset of borrowers, I also observe their housing status (own or rent), and occupation. Additional information is available on the credit profile of borrowers, such as their bank account status, amount of loans in collec-

[19] All states offer some form of e-filing options for taxpayers.

tions or charged off, and bank account lifespan. Unique identification number for loan, borrowers, and lenders is available in both data sets. This facilitates linking borrowers across different loans and different lenders. For loan applications, the underwriting decision, approved/denied, is provided, if lenders host their underwriting decisions with the credit bureau. For funded loans, I observe more information on the loans, such as loan amount, fees charged, type of loans, and also loan performance.[20]

This proprietary data set has several advantages over the data used in previous research. First, most papers on subprime lending use administrative data from one or a few lenders. Loan data from the credit bureau has the most wide coverage and includes many lenders in the industry. Second, lenders who report to the credit bureau also get underwriting information in return. This allows me to observe some of the borrowers' credit history measures. Third, this data is especially suited to study the online subprime market, which has expanding substantially in recent years, yet is still not well understood.

There are several advantages of focusing on loans from the online credit market. (1) Online credit is on average more expensive than the traditional storefront lenders. People who turn to online borrowing could be relatively more credit constrained. I will capture the population who have a high demand for credit. (2) Another key advantage of focusing on the online credit market is to avoid confounding factors from the supply side. People in different locations basically have the same access to credit, regardless of their residential address and distance to locations of financial services. This allows me to ignore the travelling distance to the physical lending sites. This helps with the identification strategy,

[20] A comprehensive report of online small-dollar credit borrowers observed in data is available here.

which relies on discontinuity in EITC generosity across state borders.

The payday loan application process does not involve a traditional credit check, and payday borrowing activity is not reported to the national credit bureaus, Equifax, Experian, or TransUnion. This means that payday borrowing is not a factor that directly affects one's traditional credit score. Although some alternative credit data vendors (for example, LexisNexis) cover this segment, it is not yet widely used for underwriting in traditional financial products. Thus, usage of small dollar credit is unlikely to affect borrowers' subsequent access to credit from other sources.[21]

To supplement the analysis and provide evidence supporting identification assumptions, I also use the Current Population Survey (CPS), and the American Community Survey (ACS) summary files at 5-digit ZIP code level. For robustness checks, I uses data on the on state level benefits of Food Stamps and unemployment benefits from various sources, and the ZIP code Business Patterns (ZCBP) for storefront lending locations.

2.6 Estimation Results

2.6.1 Summary Statistics

Among all 709 commuting zones and roughly 42,000 ZIP 5-digit (ZIP5) code areas, I include only the ZIP code areas in commuting zones that span state borders. I further impose two additional restrictions. First, only contiguous states with different state EITC benefits are included for main analysis. There are cases where there is no differences in

[21] If borrowers worry about the impact on credit scores when applying for payday loans, one might be concerned that demand for small dollar credit could be correlated with the availability of other types of liquidity from more traditional sources or demand for credit in the future, as credit score is often used for underwriting for auto loans, mortgages etc.

state EITC benefits across the border, for example, California and Nevada. These areas won't contribute to the key variations required for identification. However, I will use them for placebo analysis later in the paper. Second, only states that allow payday loans are included for analysis. For states that ban or strictly restrict payday loans, the online lending environment could be significantly different from the states where payday loans are allowed and popular.[22] It is more appropriate to consider these two different legal regimes separately.

These sample restrictions are necessary to obtain valid estimates using the identification strategy. It is also affect our interpretation of the findings. The population included in the analysis is not representative of the general population as a whole. It is only for a subset of states and for residents close to state borders. Thus, the results might not be generalizable to the entire population.

The baseline analysis uses loan level data from state-licensed online lenders. I will also show robustness analysis including offshore and tribal lenders as well, as part of robustness checks.

In addition, throughout this paper, I will show results by further limiting the sample to 5-digit ZIP code areas where the centroid distance to the state border is less than 10 kilometers or 20 kilometers.[23] Some commuting zones could be quite large in size.

[22] Storefront lenders are only allowed to operate in states that allow payday loans. However, for online lenders, there are two options. They can choose to be state-licensed and obey all state-level regulations. Or lenders could be incorporated or registered in tribal or offshore areas, which would allow them to operate even in states than ban payday loans. Due to the presence of tribal or offshore lenders, I observe loans originated for borrowers living in states that ban payday loans in the dataset. Due to the presence of these two types of lenders, we would expect the market conditions in states that ban payday loans to be very different from the other states.

[23] According to the distribution of distance to the closest state borders for 5-digit ZIP code areas, 10

Restricting distance to border could provider a subsample where residents included for analysis are more similar to each other. This also serves as a test on the sensitivity of estimates. The downside of restricting distance to state borders is a smaller sample size and thus less precise estimates.

Table 2.1 presents summary statistics for the sample used for the regression analysis. Similar to average statistics in this industry, the average loan amount is about \$450, and fees per \$100 is about \$26. 74% borrowers have a biweekly or semi-monthly pay-cycle, which means the duration of loans is on average about 15 days. The median annualized income for borrowers is around \$30,000.

2.6.2 Check on Identification Assumptions

For the identification strategy to be valid, residents in the same commuting zone should share similar characteristics and no other factors would change right at the state border. Using summary files from the ACS data, I show that characteristics are balanced at ZIP code level across borders in the same commuting zone. I run the same specification as in equation 2.3 and replace the outcome variable as ZIP code level characteristics. Dependent variable include basic demographic characteristics, such as gender, race and age, education attainment, socioeconomic characteristics, including labor force participation, income and housing, and migration. As table 2.3 shows, none of the characteristics are significantly correlated with state EITC generosity.

Other than the demographic and socioeconomic characteristics, regulations in the

---

kilometers and 20 kilometers is about 25th percentile and median of the distribution, respectively.

small dollar credit market could be different across states as well. Additionally, one might also be concerned that people in different states might have different tax filing behaviors or use of financial services. I provide additional checks on these characteristics in table B.1 and B.2 in the appendix.

2.6.3 First Stage

Table 2.2 presents the estimates from the first stage as stated in equation 2.2. To construct the outcome variable, federal and state EITC benefits, I assume that taxpayers who are eligible and have claimed federal EITC benefits will also file for state EITC benefits.

The variations in the simulated instrument are shown in figure 2.4. The difference between neighboring states could be as large as $700.

As expected, the coefficient is close to one, which is not surprising given the simulated instrument approach. R-squared is high (0.86) for the state level analysis, and lower (about 0.4) for ZIP5 level. This makes sense since there would be more confounding factors at more detailed geographic levels (ZIP5 level), which leads to a lower value for the R-squared.

2.6.4 IV Estimates

To facilitate an interpretation of the estimates, in this section I present the results from IV specification in equation 2.4. The magnitude is very similar to the reduced form results, as the first-stage estimates are close to one.

2.6.4.1 Loan Applications

Loan applications are better measures for demand for credit, as applications are not affected by lenders' underwriting policy. It is possible that lenders target certain levels for loan volume and revenues. If applications decreases in some geographic areas or during certain time of the year, lenders could potentially change underwriting policies in response to changes on the demand side.

I start with analysis using loan applications data first. Table 2.5 shows the estimates from equation 2.4 using the simulated EITC benefits as an instrument for actual amount of EITC benefits received. I show estimates using all ZIP5 areas in the CZs, and also estimates when I restrict the sample to ZIP5 within 10 km or 20k m of state borders. In table 2.5, the results imply that the effect of a \$100 increase in income leads to an 8.3% reduction in loan volume, equivalent to a reduction of eight loan applications. It is common for borrowers to apply for more than one loan annually, so I look at the number of borrowers as the outcome as well. Results show that \$100 additional EITC benefits reduces 6.6% of borrowers on average (roughly four borrowers). In terms of elasticity, a 10% increase change in EITC benefits leads to a 15.84% reduction in borrowers and a 19.42% reduction in loan applications, according to log-log specifications shown in table 2.6.

As a comparison, I also run the OLS regression using the actual amount of EITC benefits received, and the results are in table 2.4. As discussed before, OLS estimation suffers from bias due to common socioeconomic characteristics or economic shocks. One might expect people who are eligible for more EITC refunds to be more liquidity constrained and more likely to borrow, indicating a positive correlation between EITC benefits received and loan applications. From the results in table 2.4, the estimates are all positive, as expected due to the direction of bias. The OLS estimates support the direction of bias, and highlight the importance of using instruments for identification.

2.6.4.2 Originated Loans

Next I move on to the originated loans. Using originated loans adds to the results from loan application data in two ways. First, originated loans allow me to observe loan size, and analyze the effects on intensive margin as well. Second, one might worry about lenders changing underwriting in response to the changes in loan applications. However, the sample size for originated loan is smaller, which would possibly lead to larger standard errors for the estimated effects.

Table 2.7 shows that \$100 additional EITC benefits reduces the number of borrowers by 7.4% on average. This estimate is close to the estimated effects using loan applications data. However, the total number of originated loans didn't change much. This implies that borrowers who were approved have slightly more loans on average. It could be because people who still borrow in this market are relatively in need of more credit. Alternatively, lenders might have relaxed their underwriting criterion and approved more loans, given the reductions in volume of loan applications. Table 2.8 shows that the total amount of loans reduced slightly, though the estimates are not significant. And average credit per borrower might have increased, but the results on this is mixed.

In terms of dollars, given that on average each borrower receives \$587 loans each year, \$100 EITC benefits will reduce demand for loans by roughly \$36 (=\$587*6.2%) for each person.

Then I look at the default rate among all originated loans.[24] When interpreting the estimated effects on the default rate, we need to keep in mind the caveat that the composition of borrowers could have changed as a results of the EITC benefits. On average, lenders have a default rate of 26.3%. Table 2.9 shows that $100 additional EITC benefits reduce the default rate by 1.5 percentage point for state-licensed lenders. This indicates that borrowers with additional liquidity are more likely to pay off loans on time. It helps to prevent borrowers from paying extra late fees or interest, and reduces loss for lenders as well.

2.6.4.3 Discussion

Using log-log specification, we can estimate the elasticity of loan applications to EITC benefits. From table 2.6, we have an estimate of -1.94, higher than one in the absolute value. Using the estimates from originated loans in table 2.8, we have an elasticity of -1.37 for the total amount of credit, though it is not precisely estimated. Overall, the empirical estimates suggest that people are quite sensitive to income shocks.

Taking all results together, with additional income due to more generous EITC benefits, we observe less people applying for loans and less number of loans originated. On the other hand, the average amount of credit per borrower might have increased slightly. It is possible that the marginal borrowers who could benefit from additional income are more likely to be less risky and demand less credit in this market.

[24] The measure of default here depends on lenders' reporting. A caveat is that lenders could report "default" status for loans differently or selectively due to accounting purpose and lag in reporting time to credit bureau.

On Income Elasticity

One might be interested in deriving the income elasticity of demand for credit from the previous estimates. Although the elasticity estimated from the previous section is informative to some extent, there are a few challenges to derive income elasticity from these estimates. The difficulties come from inaccurate measures of total income and total amount of credit. For example, income in credit bureau data is self-reported and is subject to misreporting. The tax refund data is at aggregated level and income information could be inaccurate for nonfilers and the self-employed population. Credit (or debt) is harder to measure. Given the small loan size in the consumer credit market, even small measurement errors could result in imprecise estimates.

Nevertheless, I proceed with some rough estimates of the the income elasticity of demand for credit. the income elasticity of demand for credit can be defined as

$$\epsilon = \frac{\Delta \$debt/\$total\ debt}{\Delta \$income/\$total\ income} = \frac{\Delta \$debt/\Delta \$income}{\$total\ debt/\$total\ income} \tag{2.5}$$

Using the estimates from the previous section, we know that an additional \$100 EITC benefits reduced loan amount applied roughly by \$36. We can use 0.36 (=\$36/\$100) as a proxy for the numerator of the elasticity. Using statistics from the Federal Reserve, household debt service payments and financial obligations as a percentage of disposable personal income is about 25.42%. If we use this ratio to approximate the debt-to-income ratio, the income elasticity of demand for credit would be 1.42.

On Liquidity Constraints

The estimates provide some suggestive evidence on whether EITC recipients are liquidity constraint. Without any liquidity constraint and any frictions in credit market, individuals would choose the optimal consumption and debt (or savings) to maximize their utility over lifetime. In this case, if their income changes temporarily, individuals would smooth consumption by spreading out the transitory changes in income over time, according to the permanent income hypothesis. Individuals would also have no incentives to change their financial portfolio, as spending using credit cards or the additional income is equivalent.

However, this paper finds that use of small dollar credit reduces significantly when additional income is available. This finding suggests that individuals face high costs when borrowing and EITC recipients face imperfect capital market.

On Savings of Financial Costs

Reduction in use of small dollar credit could save individuals financial charges, including interest, late fees, and possible roll-over charges. If loan amount is reduced by $50 for an additional $100 EITC benefits, using a average fee of $26 per $100 loan, each individual would save $13 on interest fee alone. Since the default rate is also reduced, adding the potential savings on late fees, the savings on financial costs would be larger.

2.6.5 Robustness Checks

As a placebo test, I implement a permutation test by randomly assigning state EITC generosity. For all the states that allow payday loans, I assign each state a random draw from the distribution of the simulated instrument constructed using equation 2.1 and run the same specification using this randomly assigned instrument. I repeat this 2000 times. The distribution of t-statistics of this exercise is shown in figure 2.5. It is close to a normal distribution. The true estimates in the previous section is significant at 5% level in this empirical distribution.

I also run several robustness checks to show that the estimates in this paper are not sensitive to additional controls or alternative specifications.

First, as state policies or other state-level factors might be correlated with the cross-sectional differences in state EITC top-up rates, I include several additional state level controls, such as minimum wage, SNAP benefits and unemployment benefits. The results are in the top panel of table 2.10. Overall, the magnitude of the estimates do not vary much when additional state level controls are included. This helps to mitigate concerns on the possibility that state level factors or policy could be correlated with the estimated effects.

Second, I also control for the number of storefront lending sites at the ZIP code level. As described above, this paper uses data from the online small dollar credit market. Storefront lending still dominates this industry. The density of stores could vary geographically and affect consumers' demand for credit online. I construct a measure of number of stores at ZIP code level from the ZIP code Business Patterns (ZCBP) data and add it to the regression as additional controls. The results are in the bottom panel of table 2.10. Again, the estimates are not much different from the baseline results.

Third, I vary the restriction on distance to state borders and zoom in/out the distance to show that the estimates are robust to this sample restriction in table 2.11. The trade-off is that we have less precise estimates and smaller cell size when zooming in on areas closer to state borders. This set of results serves as an additional check on the sensitivity of estimated effects.

2.6.6 Limitation

There are a few limitations to this study. (1) Though small dollar credit is costly and hotly debated in policies, it is still a relatively small part of household debt. Results on applications for small dollar credit might not be informative about the overall debt for an average household in the U.S.. People might use small dollar credit as a last resort. In this regard, reductions in demand for this type of costly credit might indicate that people move away from the worst financial situations.

(2) The analysis in this paper relies on the comparison among people living in the same commuting zone close to state borders. It is possible that areas close to state border are more likely to be rural and could be different from the overall population. Thus the results on this specific population might not be applicable to the wider population.

(3) Variations used for identification in this paper come from EITC. As an important refundable tax credit for working people with low to moderate income, EITC is widely known to the eligible population and has affected a wide range of outcomes, as well studied in the literature. Other income shocks, such as stimulus payments or one-time tax rebates, might induce different responses.

2.7 Conclusion

This paper presents evidence on the effect of income shocks on demand for small dollar credit. Using variations in the state EITC top-up rates and focusing on areas near state borders within the same commuting zone, I find that borrowers are very sensitive to changes in income. Preferred estimates suggest the elasticity is about -1.5 to -2. In terms of dollar values, it translates to sizable reductions in loan volume and savings in fees and interest charges. The estimates are robust to various alternative specifications and sample restrictions.

The empirical results also suggest that EITC benefits could help alleviate people's financial burdens by providing cheap liquidity. Other public programs with income benefits (e.g., unemployment insurance benefits) could also benefit their recipients in a similar way by offering alternative options to satisfy their short-term liquidity needs. For households with volatile income flows and facing frequent economic shocks, this benefit could be crucial and lead to long-term financial stability. In this respect, public programs could partly play the role of financial services in presence of credit market frictions.

One can also think about how to design pay cycles to better address the need of short-term liquidity (Parsons and Van Wesep, 2013). Employers could also step in and help workers gain access to cheaper credit over the pay cycle. For example, employers can offer flexible paycheck schedules or financial products similar to payday loans but with lower costs.[25] Similar ideas can be applied to public policies with transfer payment. For example, in early stages of EITC implementation, policy makers have proposed offering installment option to tax payers (Holt et al., 2009).

With the recent growing trends in the small dollar financial product, it is clear that households do have a high demand for short-term financial products. For the financial

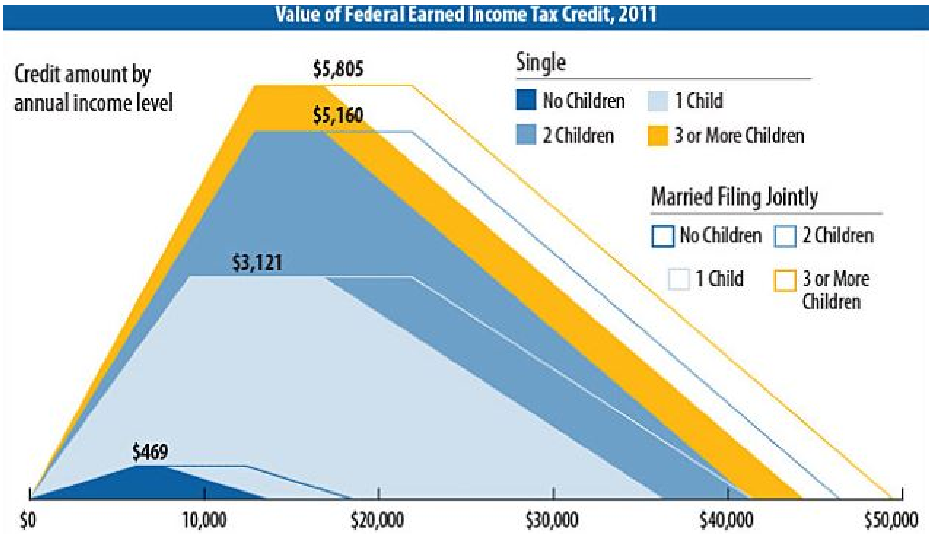
[25] Many online lenders offer flexible term repayment loans in the UK. Employers, for example, like Wal-Mart, could offer flexible timing for employees' paychecks.

industry, the results presented in this paper indicate that income could be an essential factor that affects borrowers' demand and ability to pay. Lenders might want to emphasize the role of income when building underwriting models and designing new financial products.

2.8 Figures and Tables

2.8.1 Figures

Figure 2.1

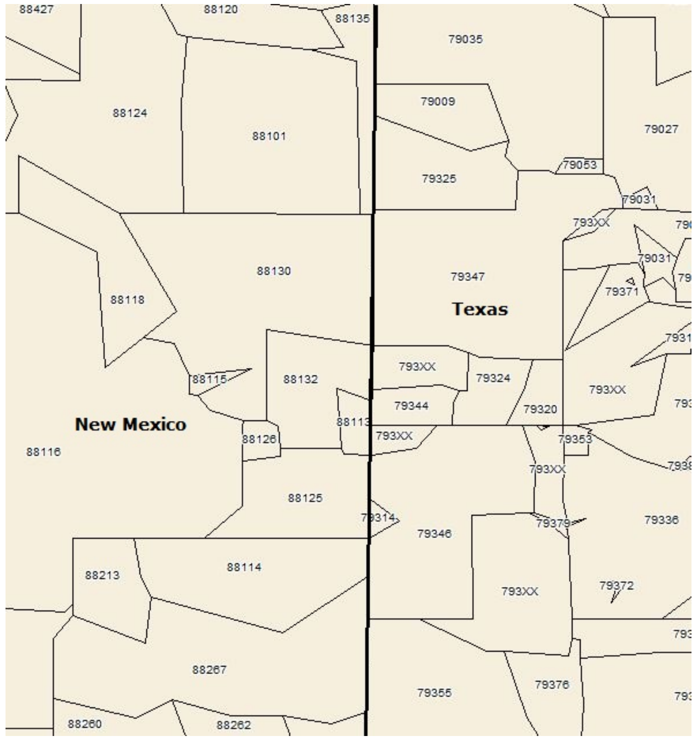


Notes: This figure shows the eligibility and generosity of federal EITC benefits in 2011, by filing status (single or married) and household size. Source: http://www.cbpp.org/research/state-earned-income-tax-credits-2010-legislative-update

Figure 2.2

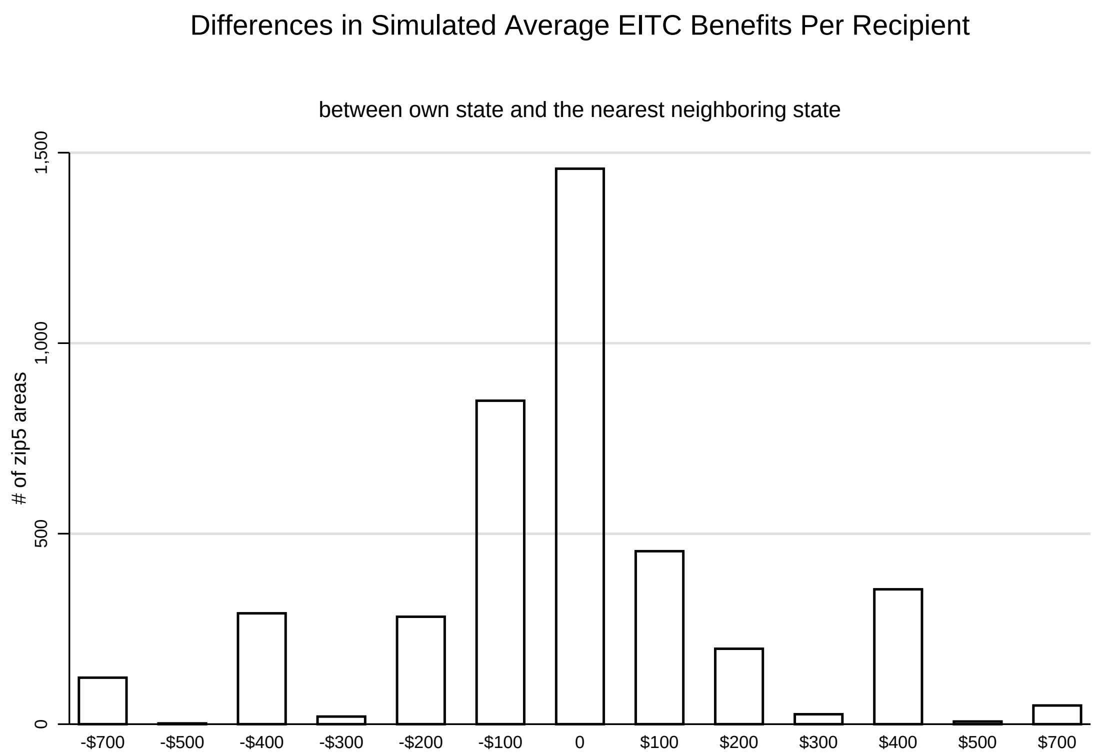
Notes: This map shows the states included for analysis. States with red dots are the states which do not offer additional state level EITC benefits. States in the blue plaid pattern are the states that offer some additional state level EITC benefits. The border areas among these two types of states provide variations for identification. States that do not allow payday loans or offer nonrefundable state EITC benefits are excluded. Border areas with the same state EITC top-up rates, for example, CA and AZ, do not contribute to identification in the baseline estimates, but will be used for placebo and robustness analysis.

Figure 2.3



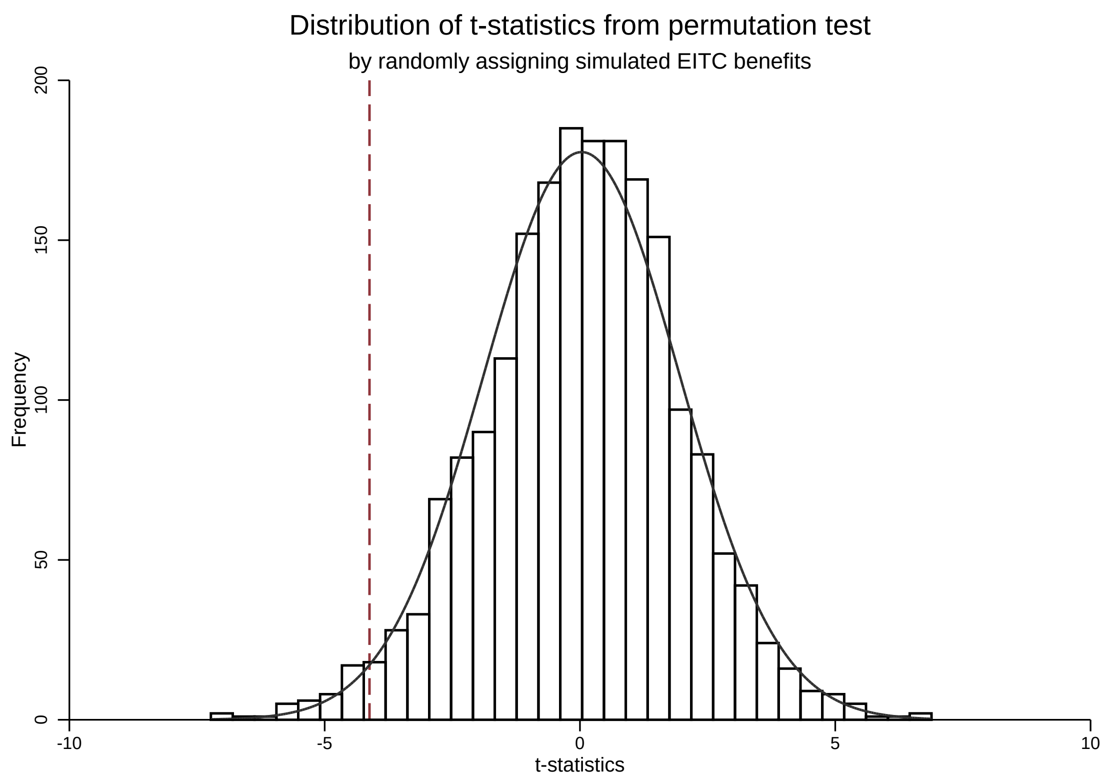
Notes: This figure provides a specific example on the identification strategy. ZIP5 areas on this map are located in two different states, New Mexico and Texas, but all belong to the same commuting zone. New Mexico offers 5% additional EITC benefits, while Texas does not offer any additional benefits. Assuming people in these areas are similar in demographic and socioeconomic characteristics, those in New Mexico would have additional income compared to the others. Using this variation in income due to state EITC policy, I analyze whether people in New Mexico would have less demand for small dollar credit.

Figure 2.4



Notes: This figure shows the distribution of simulated EITC benefits. Average EITC benefits includes both federal and state EITC in TY2011, using simulated instrument constructed from CPS data. States with nonrefundable EITC are excluded. This histogram uses ZIP5 areas in states that allow payday loans and in a commuting zone that straddles state borders.

Figure 2.5



Notes: This figure shows the distribution of t-statistics from a permutation test by randomly assigning generosity of state EITC benefits. For all the states that allow payday loans, I assigned each state a random draw from the distribution of the simulated instrument and run the reduced-form specification using this randomly assigned instrument and I repeated this process 2000 times.

2.8.2 Tables

Table 2.1: Summary Statistics

Loans	
Average \$ Loan Amount	\$446.90
Average \$ Loan Fees Per \$100	\$26.60
Average Duration of Loans (in days)	15.68
Borrowers	
Median Age	40
Median Annual Income	\$30K
Average \$ Borrowed	\$587.35
Pay Frequency	
Weekly	10%
Biweekly or Semi-monthly	74%
Monthly	16%

Note: This table shows the summary statistics on borrowers and loans observed in loan-level data.

Table 2.2: First Stage

First Stage - Simulated $EITC on Actual $EITC Received				
	State level	ZIP5 level		
Dep. Var. -Avg $EITC Received		10 km	20 km	all
Simulated Average $EITC	1.114***	1.079***	1.090***	0.992***
	(0.069)	(0.097)	(0.082)	(0.037)
Mean of Dep. Var	23.39	22.45	22.44	22.40
N	108	6919	12772	67422
R-squared	0.86	0.38	0.37	0.39

Note: The table shows the estimates of the effects of the simulated average EITC benefits per recipient on the actual EITC benefits received across states or ZIP5 areas. EITC benefits include both federal and state EITC. The federal EITC benefits received are from IRS tax return data, and state EITC benefits are calculated using the state EITC top-up rate, assuming full take-up among federal EITC filers. Regressions also include year FE (tax year 2009 - 2012), and census region FE. In total, 27 states that have refundable EITC and allow payday loan are included in the analysis (see map in figure 2.2). * p <0.10 , ** p <0.05, *** p <0.01

Table 2.3: Check on Identification Assumption

Balance in Demographic and Socioeconomic Characteristics				
	Coefficient of Log of Simulated IV			
Dep. Var.	Est.	Std. Err.	P-value	Mean of Dep. Var.
Male	-0.011	0.018	0.542	0.503
White	0.028	0.058	0.624	0.860
Median Age	2.004	3.855	0.605	40.719
High School Degree	-0.044	0.098	0.653	0.333
Bachelor Degree	0.072	0.12	0.548	0.218
In Labor Force	0.050	0.074	0.506	0.626
LnMedian Income	0.190	0.207	0.361	10.132
Below Poverty Line	-0.075	0.061	0.225	0.136
On Food Stamp	-0.021	0.022	0.347	0.035
Occupied Housing	0.032	0.077	0.682	0.853
House Ownership	0.089	0.052	0.09	0.739
Moved Last Year	0.005	0.018	0.808	0.025

Note: This table shows the coefficients of the simulated instrument from equation 2.3 on characteristics of ZIP5 areas. Data on characteristics of ZIP5 level is from ACS 2008-2012 Summary Files. The sample includes only zipcode areas in commuting zones that span state borders. Robust standard errors are clustered at the commuting zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 2.4: OLS Estimates

Effects of EITC on Loan Applications - OLS Estimates						
	#Borrowers			ln(#Borrower)		
	10 km	20 km	all	10 km	20 km	all
Average EITC	1.527*	3.872**	2.815*	0.027*	0.035**	0.034**
	(0.835)	(1.617)	(1.587)	(0.016)	(0.014)	(0.014)
Mean of Dep. Var.	109.558	107.517	82.053	3.210	3.173	2.993
N	1820	3247	6772	1820	3247	6772
Total Population	X	X	X	X	X	X
Income Distribution	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, without instrumenting $AvgEITC_{st}$ using $SimEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.5: IV Estimates(Loan Applicatoins, Level-Level Specification)

Effects of EITC on Loan Applications - IV Estimates						
		#Borrowers			ln(#Borrower)	
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-8.272**	-6.684***	-4.330***	-0.110***	-0.114***	-0.066***
	(3.340)	(2.256)	(1.629)	(0.023)	(0.022)	(0.016)
Mean of Dep. Var.	109.210	107.357	81.851	3.204	3.170	2.990
		#Loans			ln(#Loans)	
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-14.598**	-11.379**	-7.956**	-0.125***	-0.133***	-0.083***
	(7.376)	(5.301)	(3.640)	(0.026)	(0.025)	(0.022)
Mean of Dep. Var.	166.785	165.742	127.489	3.597	3.552	3.363
N	1825	3248	6769	1825	3248	6769
Total Population	X	X	X	X	X	X
Income Distribution	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows the coefficients on average EITC (in \$100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.6: IV Estimates (Loan Applicatoins, Log-Log Specification)

Effects of EITC on Loan Applications - IV Estimates						
	ln(#Borrower)			ln(#Loans)		
	10 km	20 km	all	10 km	20 km	all
ln(Avg EITC)	-2.507***	-2.535***	-1.584***	-2.812***	-2.928***	-1.942***
	(0.505)	(0.446)	(0.399)	(0.548)	(0.485)	(0.519)
Mean of Dep. Var.	3.204	3.170	2.990	3.597	3.552	3.363
N	1825	3248	6769	1825	3248	6769
Total Population	X	X	X	X	X	X
Income Distribution	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.7: IV Estimates (Originated Loans, Level-Level Specification)

Effects of EITC on Originated Loans - IV Estimates						
		#Borrowers			ln(#Borrower)	
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-2.120***	-2.591***	-1.955***	-0.098***	-0.107***	-0.074***
	(0.790)	(0.835)	(0.749)	(0.024)	(0.027)	(0.023)
Mean of Dep. Var.	17.821	17.805	13.329	2.073	2.078	1.913
		#Loans			ln(#Loans)	
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-0.745	-2.132**	-1.384*	0.016	-0.016	0.010
	(0.973)	(0.939)	(0.816)	(0.056)	(0.060)	(0.083)
Mean of Dep. Var.	43.104	41.899	30.146	2.623	2.621	2.414
N	1266	2256	4577	1266	2256	4577
Total Population	X	X	X	X	X	X
Income Distributions	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.8: IV Estimates (Originated Loans, Level-Log/Log-Log Specification)

Effects of EITC on Originated Loans - IV Estimates						
	ln($Total Credit)			ln($Average Credit)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-0.094	-0.102*	-0.062*	0.022	0.023	0.024
	(0.064)	(0.053)	(0.037)	(0.050)	(0.042)	(0.040)
Mean of Dep. Var.	8.306	8.318	8.102	6.514	6.518	6.488
	ln($Total Credit)			ln($Average Credit)		
	10 km	20 km	all	10 km	20 km	all
ln(Avg EITC)	-2.057	-2.163*	-1.368	0.452	0.489	0.540
	(1.455)	(1.174)	(0.879)	(1.159)	(0.940)	(0.933)
Mean of Dep. Var.	8.306	8.318	8.102	6.514	6.518	6.488
N	1266	2256	4577	1266	2256	4577
Total Population	X	X	X	X	X	X
Income Distributions	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.9: IV Estimates (Default Rate of Orginated Loans)

Effects of EITC on Default Rate - IV Estimates			
	10 km	20 km	all
Avg EITC	-0.012*	-0.010*	-0.015***
	(0.006)	(0.005)	(0.004)
Mean of Dep. Var.	0.270	0.271	0.263
N	1209	2157	4352
Total Population	X	X	X
Income Distribution	X	X	X
CZ FE	X	X	X
Census Region FE	X	X	X
Year FE	X	X	X

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.10: IV Estimates with Additional Controls

Effects of EITC on Loan Applications with Additional Controls- IV Estimates

Adding State Level Controls

	#Borrowers			ln(#Borrower)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-4.361	-3.372*	-3.625**	-0.103***	-0.104***	-0.061***
	(2.874)	(2.021)	(1.718)	(0.022)	(0.020)	(0.014)

	#Loans			ln(#Loans)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-7.378	-5.949	-6.702**	-0.117***	-0.121***	-0.076***
	(6.703)	(4.553)	(3.116)	(0.024)	(0.021)	(0.016)

Adding Store Location Controls

	#Borrowers			ln(#Borrower)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-6.650**	-5.275**	-3.885**	-0.111***	-0.108***	-0.063***
	(3.140)	(2.181)	(1.905)	(0.023)	(0.020)	(0.016)

	#Loans			ln(#Loans)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-10.423	-8.699*	-7.349*	-0.127***	-0.127***	-0.080***
	(7.580)	(5.172)	(3.870)	(0.025)	(0.024)	(0.022)

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table 2.11: IV Estiamtes with Varying Sample Restrictions

Effects of EITC on Loan Applications Varying Distance - IV Estimates						
	5 km	25 km	50 km	5 km	25 km	50 km
Loan Applications						
		#Borrowers			ln(#Borrower)	
Avg EITC	-8.249***	-6.319***	-5.990***	-0.129***	-0.102***	-0.070***
	(2.575)	(2.036)	(1.787)	(0.021)	(0.021)	(0.019)
		#Loans			ln(#Loans)	
Avg EITC	-12.382**	-10.928**	-10.532***	-0.142***	-0.121***	-0.087***
	(5.333)	(4.830)	(4.080)	(0.022)	(0.027)	(0.027)
Originated Loans						
		#Borrowers			ln(#Borrower)	
Avg EITC	-2.304***	-1.865***	-1.715***	-0.172***	-0.112***	-0.098***
	(0.424)	(0.356)	(0.426)	(0.050)	(0.035)	(0.033)
		#Loans			ln(#Loans)	
Avg EITC	-1.497	2.515	2.702	-0.100	-0.033	-0.009
	(1.686)	(2.675)	(2.952)	(0.076)	(0.070)	(0.071)
		ln($Total Credit)			ln($ Avg Credit)	
Avg EITC	-0.125	-0.048	-0.028	0.083**	0.086*	0.090
	(0.101)	(0.096)	(0.098)	(0.039)	(0.051)	(0.056)

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Chapter 3

Take-up of Workers' Compensation Insurance in Texas

3.1 Introduction

Workers' compensation is a large state-regulated insurance program that provides covered employees with income and medical benefits for work-related injuries or illnesses. Workers' compensation has historically been an almost universal system, with nearly all states mandating that employers provide workers' compensation insurance coverage. While states typically provide exemptions for very small employers or certain classes of workers (e.g,. agricultural or domestic workers), approximately 90% of the US workforce was covered by workers' compensation insurance in 2012.[1]

Texas is unique among US states in having never enacted a coverage mandate for workers' compensation insurance, leaving employers in Texas free to choose whether or not to participate in the state regulated workers compensation system. A worker who suffers an on-the-job injury at a subscribing employer (i.e., an employer that participates in the state workers' compensation system by purchasing insurance coverage or through self-insurance) receives workers' compensation benefits as defined by statute. In contrast, there are no statutorily defined benefits for a worker who suffers an on-the-job injury at a

[1] Sengupta, I., Baldwin, M. L., & Reno, V. (2014). Workers Compensation: Benefits, Coverage, and Costs, 2012. Washington, DC.

non-subscribing employer (i.e., an employer that has chosen not to participate in the state workers' compensation system), and such employers may be exposed to tort liability for workplace injuries. In Texas, the total payroll covered by workers' compensation insurance policies was $266 billion in 2008, which represents roughly 70% of the total Texas private industry payroll.[2]

Recently, lawmakers in several states have begun to re-evaluate their workers' compensation coverage mandates and consider systems based on the Texas model. In 2013, Oklahoma enacted a law intended to allow employers to opt out of the state workers' compensation system,[3] and a similar law was proposed during Tennessee's most recent legislative session.[4] These recent legislative actions have revived the ongoing debate about whether workers compensation insurance should be mandated. Proponents of workers compensation mandates argue that workers compensation insurance benefits workers through providing valuable recourse in the case of an on-the-job injury. Critics of workers compensation mandates argue that alternative avenues for recourse are sufficient and mandates raise firms operating costs such that workers are ultimately hurt through wage and employment cuts.

The debate over coverage mandates in workers' compensation raises several unanswered questions. Which employers are most likely to opt out of the workers' compen-

[2] Authors calculations based on the total covered payroll reported by the Texas Department of Insurance and the total payroll in Texas as estimated from the Quarterly Census of Employment and Wages published by the Bureau of Labor Statistics.

[3] Sengupta et al. (2014)

[4] Fletcher, Holly. (2015). "Bill Would Let Businesses Opt out of Workers' Compensation," The Tennessean. February 22. Available at http://www.tennessean.com/story/news/politics/2015/02/22/bill-allow-businesses-opt-workers-comp/23830533/. Accessed June 6, 2015

sation system, and how responsive is take-up of workers' compensation to the price of coverage? How do the benefits of the workers' compensation system compare to the costs of the system, and what are the efficiency implications of workers' compensation coverage mandates? Despite the importance of these questions to the emerging debate over workers' compensation coverage mandates, evidence on the determinants of employer demand for workers' compensation coverage and the economic efficiency of coverage mandates is extremely scarce. In this paper, we empirically examine employers' decision to take up workers' compensation coverage within the context of the Texas Workers Compensation system, with the aim of providing evidence on these questions.

Using unique administrative firm-level data on workers compensation coverage, we exploit variation in insurance premiums resulting from regulatory updates to analyze employer demand for workers compensation insurance. While the workers compensation insurance system is optional in Texas, premiums for workers compensation insurance are heavily regulated by the state. In particular, the government sets the relative premium rates across industries. We leverage the differences-in-differences variation in premiums induced by periodic regulatory updates of these across-industry relative rates. Our preliminary estimates suggest that a 10% increase in premiums results in a 2.2% decline in the number of firms providing workers compensation insurance and a 2% decline in the payroll covered by workers compensation insurance. The demand estimates are precisely estimated and are robust to different specifications.

Our research contributes to the broader literature on the demand for employer-provided insurance. Much of the prior work on the demand for employer-provided insurance focuses on contexts such as health insurance (e.g., Finkelstein (2002); Gruber and

Lettau (2004); Kolstad and Kowalski (2016)) and long-term care insurance (e.g., Courtemanche and He (2009)). To the best of our knowledge, our paper is the first to provide evidence on the demand for workers compensation insurance.

Our paper also contributes to the literature on workers compensation insurance. Much of the prior literature on Workers Compensation insurance relates to either the incentive effects of program features (e.g., Krueger (1990a,b); Meyer et al. (1995)) or the incidence of changes in the program (e.g., Fishback and Kantor (1995); Gruber and Krueger (1991)). We contribute to this literature by analyzing the nature of employer demand for workers compensation insurance and the potential efficiency implications of this coverage, providing evidence pertinent to the ongoing policy debate surrounding workers compensation mandates.

This paper proceeds as follows. Section 3.2 provides details on the institutional setting. Section 3.3 and 3.4 introduces the data source, and discusses the empirical strategy. Section 3.5 presents our results and discussion. Section 3.6 concludes.

3.2 Background

3.2.1 Workers' Compensation in Texas

Workers' compensation is a state-regulated insurance program that provides covered employees with income and medical benefits for work-related injuries or illnesses. With workers' compensation coverage, employers have protection from lawsuits resulting from employee job-related injuries and illnesses. Workers' compensation insurance could also encourage employers to implement additional cost-saving risk management for workplace safety. Workers' compensation is financed exclusively by employers in most states. Employers could purchase workers' compensation insurance from private insurers or a state insurance fund. Some large employers might be eligible to self-insure.

Each of the 50 states, the District of Columbia, and U.S. territories has its own workers compensation program.[5] With the exception of Texas, workers' compensation insurance coverage is effectively mandatory for employers in all states.[6] Texas private employers can choose whether or not to provide workers' compensation insurance coverage for their employees.[7]

Workers' compensation offers income benefits, medical benefits, burial benefits and death benefits. Income benefits replace a portion of any wages one loses because of a work-related injury or illness, and vary by the severity of injury and the duration of injury. Medical benefits pay for all the necessary medical care to treat your work-related injury or illness.

The cost of workers' compensation varies mostly depending on the size of total payroll, the risk of business, and history of injuries in the past. The basic premium depends on the number of employees and cost of payroll. Each category of industry, defined by the classification codes, is assigned a risk classification, which shows whether your industry or company is a high- or low-risk employer and will determine how high the pre-

[5] Separate U.S. government programs cover federal civilian employees and specific high-risk workers (energy employees, workers' exposed to radiation, veterans of military service etc.).

[6] There are limited exceptions that typically exempt employers with a small number of employees or workers in specific classifications, such as agricultural or domestic employees.

[7]However, government agencies and public institutions are required to provide workers' compensation insurance while also requiring such coverage from private employers who do business with them. Texas employers who choose to opt out of the statutory system can create their own non-subscription work-injury compensation program or offer no workers' compensation benefits or protection at all and risk catastrophic legal liability.

mium is. The initial manual premium is further adjusted with premium credits and debits, experience rating, large deductible credit, healthcare network credits, premium discount, and other factors based on the characteristics of each employer. In 2008, the average standard premium was $1.03 (per $100 payroll) for employers in Texas.

Employers who choose to have insurance may purchase workers' compensation insurance policies from private insurance companies, or self-insure. The primary benefit for employers with workers' compensation coverage is protection from potential lawsuits by employees on work related injuries. Employers without workers' compensation coverage (i.e. nonsubscribers) don't have the same legal protections as employers that provide workers' compensation coverage. If an injured employee of a non-subscriber files lawsuit and is able to prove that the injury was due to the employer's negligence, the non-subscriber could be subject to high damage awards. The non-subscriber might also be required to pay defense-related legal expenses.

Employers choose to opt out of workers compensation insurance coverage for a variety of reasons. Texas nonsubscribers can choose to provide additional benefits to their workforce or work with health care professionals to develop programs to provide quality care at a reasonable cost. Nonsubscribers can also customize their occupational injury benefit plan to reduce the costs of work-related injuries.

In 2012, 67% of employers chose to purchase workers compensation insurance, which covers 81% of workers in Texas. The cost of workers compensation could vary substantially by industry and employer size. Large employers are more likely to take up workers' compensation insurance. The take-up rate is higher for industries with relatively high risks, such as mining, utility construction and manufacturing.

3.2.2 Insurance Market and Premium

Texas employers can obtain workers' compensation coverage through self-insurance, purchasing a workers' compensation policy, or joining a workers' compensation insurance pool.

As of January 1, 1993, employers who meet certain safety and financial requirements may apply to be a certified self-insured employer in Texas. Self-insurance allows an employer to assume the risk for the vast majority of its workers' compensation liability, and purchase some form of excess or stop-loss coverage to protect the employer from catastrophic losses.[8]

In the standard insurance market, more than 270 insurance companies had positive written premiums for workers' compensation insurance in 2011. The total direct written premiums for the workers' compensation insurance market was about $2.16 billion in Texas. The top 10 insurance company groups write 81.7% of the market and the top writer, Texas Mutual Insurance Company, has 33.8% of the market based on the written premium in 2011.[9]

All workers' compensation insurance companies follow a very similar approach

[8] Self-insurance provides employers with greater control over claims and disability management, and also provides loss-control incentives for employers to promote workplace safety. To be eligible for the certified self-insured program, private employers need to have an estimated unmodified manual insurance premium of at least $500,000 in Texas , or at least $10,000,000 nationwide, and meet other qualifications. As of January 1, 2016, there are about 130 employers who are self-insured. A detailed list of self-certified employers could be found this link at the TDI

[9] Texas Mutual, formerly the Texas Workers' Compensation Fund, wrote nearly $730 million in direct written premiums. The Legislature created Texas Mutual in 1991 to serve as a competitive force in the marketplace, to guarantee the availability of workers' compensation insurance in Texas, and to serve as an insurance company of last resort. While Texas Mutual is the insurer of last resort, it predominately writes voluntary business, competing with the rest of the workers' compensation market.

to calculating the premium for workers' compensation insurance coverage. The cost of workers' compensation varies mostly depending on the number of employees, risk of the business, and history of injuries in the past.

The basic premium depends on the classification of employees and the size of payroll. Each industry is assigned a risk classification. The classification code shows whether your industry or company is a high- or low-risk employer and will determine how high the premium is.[10]

Some kinds of work naturally have a higher exposure to risk for workplace injuries. Each classification code has a corresponding premium rate (i.e. manual rates) based on each $100 of payroll. For example, clerical workers (classification code 8810) have lower risks of injury and benefit payments and thus a lower manual rate is applied compared to a higher risk group such as construction workers (classification code 7538). Using the rates published by the Texas Department of Insurance in 2006, the manual rate for clerical workers was 0.46 (46 cents per $100 payroll), while that for construction workers was 22.66.[11]

Insurers can calculate the manual premium by multiplying the rate for a classification by payroll (per $100 dollars). If the liability limit is increased, expected future benefits will also proportionally increase.[12] Therefore, costs associated with an increased

[10] The code for each company is based on statistics compiled by the National Council on Compensation Insurance (NCCI), which tracks statistics gathered by hundreds of insurance carriers in several states.

[11] Some occupations are common to so many businesses that special classifications have been established for them. These special classifications are called standard exception classifications. Employees within the definition of a standard exception classification are not included in a basic classification unless the basic classification specifically includes those employees.

[12] The most common liability limit chosen by Texas employers is $1 million.

liability limit are applied to the manual premium.

The initial manual premium is further adjusted with experience rating using experience modification factors (or experience modifier), which are designed to give businesses a financial incentive for maintaining safer workplaces. The experience modification factor predicts an employer's future losses by looking at their past loss experience. This experience modifier shows whether one company's losses from employee compensation benefits are at, above or below average and is multiplied by the company's manual premium to determine the employee compensation rate. The experience modifier is re-calculated each year using the combined claims from a three-year rolling period.[13]

Employers could reduce the premium by choosing large deductible plans. Deductible plan credits amounted to almost $1.5 billion in 2008, representing about a 30% discount of the modified premium.[14]

Insurers have the option to adjust rates further using the schedule rating or modeled rating factors. Schedule rating is an optional rating plan that carriers may file which allows the carrier to deviate from their filed rates based on the individual characteristics of a risk. For example, insurers can assign credits for an automated work environment or

[13] Some employers with higher than average injury experience may see their manual premium increase via an experience rating modifier that is greater than 1. Small employers can also benefit from the Premium Incentive for Small Employers program that requires credits, discounts and surcharges for small employers based on their most recent one to two years of experience. For example, an employer who falls within the average range would typically get an experience modification factor of 100 and would be charged the full base rate. On the other hand, an employer with an experience modification factor of 90 might see a 10% savings, while an employer with a factor of 110 would pay 10% more. Experience modification factors have a direct impact on premium rates and create incentives for each company to work to reduce workplace accidents.

[14] Large deductible plans are those policies with a deductible amount of $100,000 or more. As a result, large deductible plan discounts are mostly for medium to large employers who are willing to pay out-of-pocket expenses up to the deductible amount.

safety officers on staff, and assign debits for hazardous machinery. The modeled rating factor is an optional multiplicative factor, which takes into consideration individual risk characteristics and the loss experience of the insured employer.

To offer incentives for containing medical costs of injured works, a healthcare network credit could be applied to the policies. An insurance carrier can either establish its own network for certification or can contract with a network that has been certified.[15]

In addition, there will be a premium discount, based on the size of the premium. The premium discount recognizes that the relative expense of issuing and servicing larger premium policies is less than for smaller premium policies.

Finally, each policy is subject to an expense constant and terrorism premium debit, which is a premium charge which applies to every policy in addition to the premium. It covers expenses such as those for issuing, recording and auditing, which are common to all workers' compensation policies regardless of premium size.

To summarize, insurers start with the risk classification of employees and the size of total payroll to calculate the manual rates, and further adjust the initial premium based on the past claims of the employer, features of the insurance policy, individual characteristics of the employer, and other surcharges. In 2008, the average standard premium was \$1.03 (per \$100 payroll) for employers in Texas. Theoretically, a 1% change in the manual rates (or relativity) would lead to a 1% increase in premium for employers, holding other factors constant.

[15] The Texas Department of Insurance (TDI) anticipates that certified workers' compensation health care networks will help reduce the cost of workers' compensation claims in Texas and that the cost savings should be passed on to policyholders participating in the networks in the form of a premium credit.

3.3 Empirical Strategy

3.3.1 Identification

To identify the causal effect of price on the take-up of workers' compensation coverage, we need to isolate exogenous variation in premium. Given the differences across industry and business cycles in the insurance market, analysis using cross-sectional or time-series data alone could be problematic and suffer from endogeneity problem.

As described in section 2.3, insurers take into account both industry specific and firm specific risks when calculating the premium for each policy. To overcome the endogeneity issue, this paper takes advantages of cross-industry and cross-year variation in the manual rates that are used as the initial input of premium calculations. Based on the formulas for pricing insurance policies, 1% increase in manual dates should translate to 1% increase in premium.

The manual rates are frequently updated by the Texas Department of Insurance and vary substantially across industry and over time. The variation in manual rates are mostly driven by industry-level claim history from the past five years with a three-year lag, and adjustments due to budget concerns. More importantly, the manual rates are not correlated with individual firm's own specific risk. In addition, using manual rates allow us to overcome the issue the actual premium is not observed for firms that choose to opt out of workers' compensation coverage.

3.3.2 Estimating Equations

Let i represent industry and t represents time period. The main regression is specified as follows:

$$y_{it} = \alpha + \beta r_{it} + \delta_i + \theta_t + \lambda_i t + \epsilon_{zt} \tag{3.1}$$

where y_{it} is the dependent variable and r_{it} is the relativity. The specification includes time period fixed effects (θ_t), industry (measured by classification, NAICS or SIC codes) fixed effects (δ_i), and industry-specific time trends ($\lambda_i t$).[16]

To measure the coverage of workers' compensation insurance, we use the number of covered firms in industry i and time t, and the number of newly covered firms in industry i and time t as the outcomes of interest.[17] We also look at outcomes such as the total covered payroll in industry i and time t to measure coverage in terms of dollars.

3.4 Data

The data for this project come from difference sources. The manual rates of workers' compensation and subscriber data are from the Texas Department of Insurance (TDI). TDI published relativities (or manual rates), covered payroll and total costs for each classification for each policy year (PY).[18] Data on covered payroll and costs are available from 1993 to 2011, and relativities are available from 1999 to 2015. Subscriber data is at policy level from 2005 to 2013, with information on employers, including the Federal

[16] For some of the results reported, we include industry specific trend at 3-digit classification level. In our sample, there are about 360 distinct 4-digit classification codes, and about 240 distinct 3-digit classification codes.

[17] Workers' compensation insurance policies are originated throughout the year. From our analysis of subscriber data, the timing of policy origination and renewal doesn't seem to be correlated with changes in the relativities.

[18] Policy year differs from calendar year because firms don't necessarily have to start insurances coverage in the beginning of each calendar year. From the subscriber data, about 13% of firms have policy effective dates in January, and the rest of the firms have policies originated throughout the year.

Employer Identification Number (FEIN), name, and address, classification code, policy effective date, and policy expiration date.

For our analysis, we aggregate the policies to quarterly-classification or yearly-classification level and match with the relativities for each classification in the policy year to examine the effect on the number of subscribers. We also look at the covered payroll and costs at policy-year and classification level.

Table 3.6 shows examples of relativities for several classifications with large payroll size. Relativities vary substantially across industries. For high-risk classification, such as roofing and construction, manual rates are above 20, which means the costs of injuries on the job is more than \$20 for each \$100 payroll. On the other hand, for low-risk classifications, such as clerical office employees, the costs of injuries for each \$100 payroll is as low as \$0.46.

A full list of relativities by the date of update is shown in table 3.5. Panel A shows the mean and percentiles of relativities. Panel B shows the mean and percentiles of relativities normalized by the average relativities each year. The level of relativities are adjusted down across-the-board by 7% in 2005, 2008, and 2011, and by 10% in 2009.

The relativities vary over time as well. Figure 3.1 shows the histogram of year-to-year changes in relativities separately for years without re-basing and with re-basing. The changes are capped at 25% for all years. For years with across-the-board reductions, relativities for all industries are shifted down by 7% or 10%.

Table 3.4 shows the covered payroll, average manual rates and average premium by year. Average manual rates and average premium are measured in terms of \$100 payroll. The size of covered payroll increased over time. Average manual rates and average premium were highest in the early 2000s and have decreased slightly in recent years.

Table 3.1 presents the take-up rate over time in Texas from 2001 to 2012. Around 65% of employers chose to purchase workers' compensation insurance, which covers about 80% of workers in Texas. Take-up rates vary by the size of employers and the industry. As shown in table 3.2, large firms are more likely to purchase insurance with take-up rates above 80%. Firms in industries with higher risk of work-related injuries are more likely to have coverage, such as mining, utilities construction and manufacturing, as shown in table 3.3.

3.5 Estimation Results

To examine the effect of premium on the take-up decision, table 3.7 shows the estimates on the number of covered firms and the number of newly enrolled firms, using the specification in equation 3.1. We consider two separate time periods, from 2005 to 2011 and from 2005 to 2013.[19] The first and third column include classification fixed effects and time (in quarters) fixed effects, and the second and fourth column include also classification specific time trends. We find that a 10% increase in relativities reduces the number of newly enrolled firms by 2%. The effect on the number of covered firms are similar. The estimates imply that the price elasticity of demand for workers' compensation insurance is modest, with magnitude around -0.2.

Table 3.8 reports the results from similar regressions using annual level data. The

[19] The time period from 2005 to 2011 matches with the availability of data on covered payroll and costs.

magnitude of the estimates are slightly larger. We find that 10% increase in relativities reduces the number of newly enrolled firms by 2.9%, and the number of covered firms by 2.6%.

To also account for the differences in firm size, table 3.9 examines the effect on the covered payroll. We find that a 10% increase in relativities reduces the total covered payroll by 2%.

3.5.1 Robustness Check

One robustness check takes advantage of the fact that relativities are not changed by more than 25% in either direction (see figure 3.2). If the changes in outcome variables are driven by other changes in the industry correlated with the update but not related to premium, then we would expect to see changes in the outcome variables associated with the hypothetical unconstrained relativities above and beyond correlation with the actual relativities. We run the following specifications to test this empirically:

$$y_{it} = \Sigma_{p=1}^{\overline{p}} \left\{ \beta_p (\tilde{r}_{it})^p + \gamma_p (\tilde{r}_{it})^p \mathbb{1}(\tilde{r}_{it} > 1.25 r_{i,t-1} | \tilde{r}_{it} < 0.75 r_{i,t-1}) \right\} + \delta_i + \theta_t + \lambda_i t + \epsilon_{it}. \tag{3.2}$$

where $\tilde{r}_{it}$ is the counterfactual relativity assuming there were no bound on the possible update (uncapped or raw relativity), and p is the degree of the polynomial. If the identification assumption for the baseline difference-in-differences holds, then we should expect the estimated coefficients of the interaction terms (γ) to be insignificant and close to zero.

Table 3.10 shows the results on the number of covered firms using levels of relativity and cubic polynomial terms. As expected, the estimated coefficients of the interaction terms are not significant. We have also looked at covered payroll and estimated similar specifications using log of relativity, and have the insignificant interaction terms. This set of robustness check suggest that the change in coverage are from the actual relativities that are regulated by TDI, rather than the changes in costs or in the industry that are not correlated with premium.

3.6 Conclusion

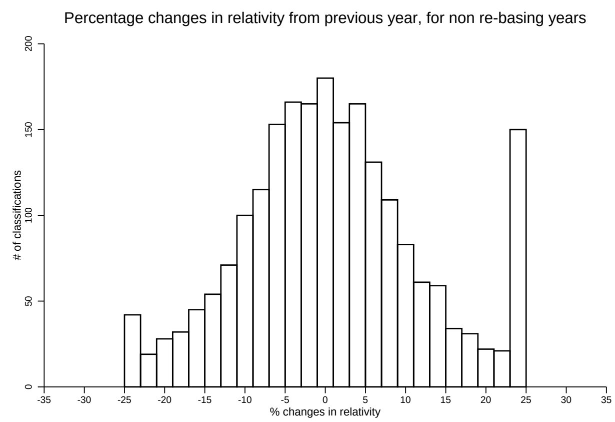
This paper empirically examines the take-up of workers' compensation insurance coverage by employers in Texas, using variation in premium from regulatory updates. We find that a 10% increase in regulated premium reduces the number of covered firms by 2%. The effect on covered payroll is similar. These estimates suggest a modest price elasticity of demand for workers' compensation insurance coverage of -0.2, comparable to the estimates of price elasticity of demand for health insurance by employers in the literature.

Although the firm-level data do not allow us to disentangle the effects of the number of covered workers and implement full welfare analysis, we rely on the size of covered payroll to account for differences in firm size. Going forward, with more detailed firm-level data on wages and employment, we could get a better understanding of the welfare implications of mandates for workers' compensation insurance coverage. We also plan to further examine the selection in the insurance market by looking at different risk groups and heterogeneity by firms' characteristics.

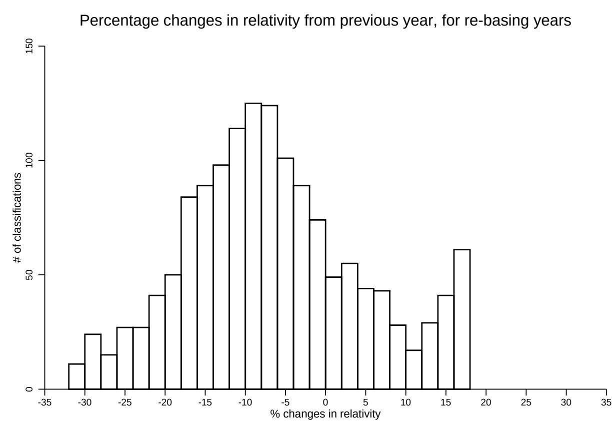
3.7 Figures and Tables

3.7.1 Figures

Figure 3.1: Variation in Relativites



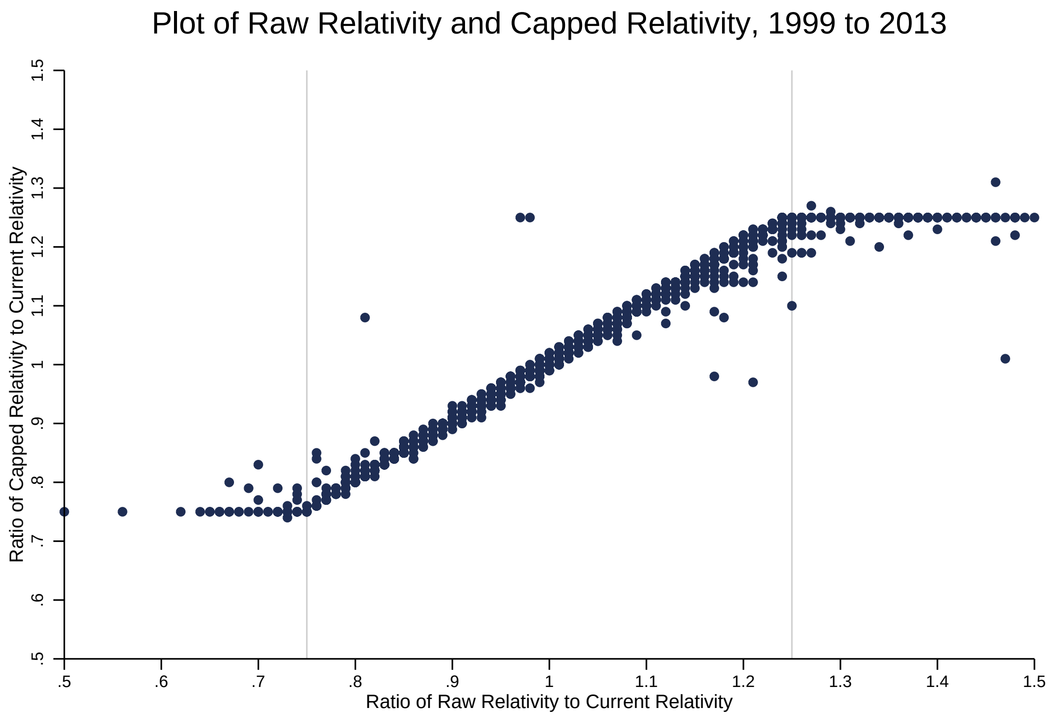
(a)



(b)

Notes: This figure shows the percentage changes in relativity relative to the previous year. Changes in relativities are capped at 25%, before any across-the-board adjustment. The top panel shows the changes for non-rebasing years. In the bottom panel, relativities for all classifications are reduced by 7% in 2005, 2008 and 2011, and by 10% in 2009.

Figure 3.2: Raw Relativity v.s. Capped Relativity



Notes: This figure shows the scatter plot of raw relativity and the capped relativity from 1999 and 2013. The horizontal axis represents the ratio of raw relativity to current relativity. Current relativity is the regulated relativity in effect from last update (typically last year). The vertical axis represents the ratio of capped relativity to current relativity, where the ratio is capped at .75 and 1.25.

3.7.2 Tables

Table 3.1: Take-up Rates of Workers' Compensation in Texas

	% employers	% workers
2001	65%	84%
2004	62%	76%
2006	63%	77%
2008	67%	75%
2010	68%	83%
2012	67%	81%

Source: The take-up rate estimates in 2001 are from the Research and Oversight Council on Workers' Compensation and Public Policy Research Institute; and estimates from 2004 to 2014 are from the Texas Department of Insurance Workers' Compensation Research and Evaluation Group and Public Policy Research Institute.

Table 3.2: Take-up Rates of Workers' Compensation by Employer Size

# of Employees	2001	2004	2006	2008	2010	2012	2014
1-4	53%	54%	57%	60%	59%	59%	57%
5-9	71%	63%	64%	69%	70%	71%	73%
10-49	81%	75%	74%	77%	80%	81%	79%
50-99	84%	80%	81%	82%	84%	81%	82%
100-499	87%	84%	83%	84%	87%	88%	86%
500+	86%	80%	79%	74%	85%	83%	81%

Source: The take-up rate estimates in 2001 are from the Research and Oversight Council on Workers' Compensation and Public Policy Research Institute; and estimates from 2004 to 2014 are from the Texas Department of Insurance Workers' Compensation Research and Evaluation Group and Public Policy Research Institute.

Table 3.3: Take-up Rates of Workers' Compensation by Industry

Industry Type	2004	2006	2008	2010	2012	2014
Agriculture, Forestry, Fishing, Hunting	61%	75%	73%	75%	71%	74%
Mining, Utilities Construction	68%	79%	72%	81%	78%	80%
Manufacturing	58%	63%	69%	69%	71%	75%
Wholesale Trade, Retail Trade, Transportation	60%	63%	71%	68%	74%	66%
Finance, Real Estate, Professional Services	68%	67%	67%	67%	68%	71%
Health Care, Educational Services	59%	56%	61%	68%	65%	59%
Arts, Entertainment, Accommodation, Food Services	46%	48%	54%	60%	60%	61%
Other Services Except Public Administration	61%	58%	64%	58%	51%	53%

Source: The take-up rate estimates in 2001 are from the Research and Oversight Council on Workers' Compensation and Public Policy Research Institute; and estimates from 2004 to 2014 are from the Texas Department of Insurance Workers' Compensation Research and Evaluation Group and Public Policy Research Institute.

Table 3.4: Covered Payroll, Manual Rates and Average Premium by Year

Policy Year	Covered Payroll	Manual Rates	Average Premium
2000	194,641,734,299	2.77	1.27
2001	199,930,429,576	2.93	1.32
2002	194,358,418,377	3.30	1.52
2003	198,085,623,131	3.20	1.66
2004	204,233,950,515	3.17	1.60
2005	222,110,691,113	2.92	1.43
2006	241,285,770,452	2.80	1.36
2007	265,757,149,487	2.58	1.18
2008	265,918,225,355	2.23	1.03

Note: Manual rates and average premium are measured for each $100 payroll. *Source*: Costs to Employers and Efficiencies In the Texas Workers Compensation System, Texas Department of Insurance, Workers Compensation Research and Evaluation Group, 9/1/2011.

Table 3.5: Relativities by Date of Update

Panel A: relativities						
Date	Mean	10th PCTL	25th PCTL	50th PCTL	75th PCTL	90th PCTL
1/1/1999	8.78	2.32	4.25	7.23	10.84	17.46
1/1/2000	8.69	2.42	4.47	7.31	10.64	16.51
1/1/2001	8.63	2.44	4.54	7.37	10.51	15.90
1/1/2002	8.69	2.36	4.48	7.56	10.69	15.69
1/1/2003	8.63	2.39	4.66	7.43	10.57	15.21
1/1/2005	7.94	2.29	4.32	6.96	9.60	14.95
1/1/2006	7.91	2.31	4.36	6.82	9.58	15.34
3/1/2007	7.87	2.21	4.40	6.87	9.73	14.38
1/1/2008	7.42	2.07	4.11	6.48	9.27	12.87
5/1/2009	6.74	1.74	3.63	5.84	8.39	11.94
6/1/2011	6.28	1.68	3.33	5.47	7.82	11.42
6/1/2013	6.07	1.63	3.33	5.37	7.52	10.75

Panel B: relativities (normalized)						
Date	Mean	10th PCTL	25th PCTL	50th PCTL	75th PCTL	90th PCTL
1/1/1999	1	0.26	0.48	0.82	1.23	1.99
1/1/2000	1	0.28	0.51	0.84	1.22	1.90
1/1/2001	1	0.28	0.53	0.85	1.22	1.84
1/1/2002	1	0.27	0.52	0.87	1.23	1.80
1/1/2003	1	0.28	0.54	0.86	1.22	1.76
1/1/2005	1	0.29	0.54	0.88	1.21	1.88
1/1/2006	1	0.29	0.55	0.86	1.21	1.94
3/1/2007	1	0.28	0.56	0.87	1.24	1.83
1/1/2008	1	0.28	0.55	0.87	1.25	1.73
5/1/2009	1	0.26	0.54	0.87	1.24	1.77
6/1/2011	1	0.27	0.53	0.87	1.25	1.82
6/1/2013	1	0.27	0.55	0.88	1.24	1.77

Note: The above table lists the mean and percentiles of the percentage updates to relativities, across classification level observations. Panel A displays summary statistics for the actual relativity updates. Panel B displays summary statistics for the relativity updates, normalized to the annual average of each year.

Table 3.6: Selected Examples of Relativities in 2006

Classification	Description	2003 Payroll	Relativity
7538	electric light or power line construction & drivers	$ 94,342,002	22.66
5551	roofing - all kinds - & yard employees, drivers	$ 79,394,461	21.07
6202	oil or gas well & drivers	$ 634,795,692	16.60
7219	trucking: noc - all employees & drivers	$ 1,890,757,258	14.43
3724	machinery or equipment erection or repair & drivers	$ 1,121,976,247	7.09
8748	automobile salespersons	$ 1,411,568,846	0.85
8832	physician & clerical	$ 4,923,987,040	0.75
8742	salespersons, collectors or messengers - outside	$ 15,661,961,713	0.74
8809	executive officers noc - outside duties	$ 4,990,449,649	0.62
8810	clerical office employees noc	$ 76,587,441,705	0.46

Source: Relativites and covered payroll are published by the Texas Department of Insurance.

Table 3.7: The Effects of Relativities on Covered Firms

Dependent Var.: ln(# firms newly enrolled$_{it}$)				
ln(relativity$_{it}$)	-0.168**	-0.208***	-0.158**	-0.175***
	(0.075)	(0.065)	(0.064)	(0.059)
N	9205	9205	11841	11841
Mean of Dep. Var.	4.243	4.243	4.247	4.247
Dependent Var.: ln(# firms enrolled$_{it}$)				
ln(relativity$_{it}$)	-0.227***	-0.215***	-0.222***	-0.202***
	(0.062)	(0.056)	(0.052)	(0.054)
N	9205	9205	11841	11841
Mean of Dep. Var.	4.481	4.481	4.524	4.524
Classification FE	X	X	X	X
Time FE	X	X	X	X
Classification specific trend		X		X
Level of Aggregation				
i represents	classification	classification	classification	classification
t represents	quarter	quarter	quarter	quarter
Included Time Span	PY 2005-2011	PY 2005-2011	PY 2005-2013	PY 2005-2013

Note: This table shows estimates on the number of firms enrolled and the number of firms newly enrolled using specifications from equation 3.1. Data is at the classification-year level from 2005 to 2013. Standard errors are clustered at the classification level.

Table 3.8: The Effects of Relativities on Covered Firms (Annual)

Dependent Var.: ln(# firms newly enrolled$_{it}$)				
ln(relativity$_{it}$)	-0.259*	-0.285**	-0.285**	-0.235**
	(0.139)	(0.116)	(0.111)	(0.104)
N	2497	2497	3211	3211
Mean of Dep. Var.	5.362	5.362	5.362	5.362
Dependent Var.: ln(# firms enrolled$_{it}$)				
ln(relativity$_{it}$)	-0.320***	-0.261***	-0.322***	-0.238***
	(0.082)	(0.075)	(0.074)	(0.076)
N	2498	2498	3212	3212
Mean of Dep. Var.	4.772	4.772	4.815	4.815
Classification FE	X	X	X	X
Time FE	X	X	X	X
Classification specific trend		X		X
		X		X
Level of Aggregation				
i represents	classification	classification	classification	classification
t represents	year	year	year	year
Included Time Span	PY 2005-2011	PY 2005-2011	PY 2005-2013	PY 2005-2013

Note: This table shows estimates on the number of firms enrolled and the number of firms newly enrolled using specifications from equation 3.1. Data is at the classification-year level from 2005 to 2013. Standard errors are clustered at the classification level.

Table 3.9: The Effects of Relativities on Covered Payroll

Dependent Var.: ln(total covered payroll$_{it}$)				
ln(relativity$_{it}$)	-0.237***	-0.199*	-0.281***	-0.069
	(0.087)	(0.105)	(0.075)	(0.078)
N	2394	2394	4519	4519
Mean of Dep. Var.	18.122	18.122	17.976	17.976
Classification FE	X	X	X	X
Time FE	X	X	X	X
Classification specific trend		X		X
Level of Aggregation				
i represents	classification	classification	classification	classification
t represents	year	year	year	year
Included Time Span	PY 2005-2011	PY 2005-2011	PY 1999-2011	PY 1999-2011

Note: This table shows estimates on total covered payroll using specifications from equation 3.1. Data is at the classification-year level from 1999 to 2011. Standard errors are clustered at the classification level.

Table 3.10: Robustness Analyses: Workers' Compensation Demand

	ln(#firms enrolled$_{it}$)		ln(#firms newly enrolled$_{it}$)	
RawRelativity	-0.047**	-0.053**	-0.045*	-0.061***
	(0.021)	(0.021)	(0.023)	(0.020)
RawRelativity^2	0.001	0.002	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)
RawRelativity^3	-0.000	-0.000*	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Capped*RawRelativity	-0.015	-0.013	-0.016	-0.016
	(0.011)	(0.009)	(0.013)	(0.012)
Capped*RawRelativity^2	0.002	0.001	0.002	0.003*
	(0.001)	(0.001)	(0.001)	(0.001)
Capped*RawRelativity^3	-0.000	-0.000	-0.000	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)
Classification FE	X	X	X	X
Year FE	X	X	X	X
Class-specific trend		X		X
F-test of interaction terms				
P-value	0.551	0.484	0.458	0.136
Level of Aggregation				
i represents	classification	classification	classification	classification
t represents	quarter	quarter	quarter	quarter
Included Time Span	PY 2005-2013	PY 2005-2013	PY 2005-2013	PY 2005-2013

Note: This table shows estimates on number of firms enrolled or newly enrolled using specification in equation 3.2. Raw relativity is the relativity without the 25% cap on changes in relavitiy update. Capped is an indicator for the classification-quarter observations where the relavitiy updates are higher than 25% in either direction. Data is at the classification-quarter level from 2005 to 2013. Standard errors are clustered at classification level.

Appendices

Appendix A

Appendix: Financial Incentives and Physicians' Behavior

A.1 Data Construction

Texas Workers' Compensation Medical Claims Data

Texas Workers' Compensation Medical Claims Data is obtained from the Texas Department of Insurance.[1] The data file for professional services contains billing information for doctors and other healthcare professionals, including ambulatory surgical centers (ASC). For each quarter, it includes a header and detail file. The header file contains billing level information, including provider information and diagnosis, and the detail file contains itemized service level information, such as HCPCS codes and place of services.

Texas Physicians Registry Data

Texas Physicians Registry Data is available from Texas Medical Board, and includes all Texas-licensed physicians, current and non-current (deceased, retired, etc.). Information includes unique ID, license number, name, mailing address, practice address, birth year, birthplace, medical school, graduation year, license issuance date, license expiration date, registration status code and date, county name, gender code, and ethnicity code. Also includes degree, primary and secondary specialty, method of licensure,

[1] Details on professional services public use data can be found at this link.

state/country of reciprocity, practice type code, practice setting code, and practice time code fields.

For each medical bill, there is a billing provider or (and) rendering bill provider reported. In the case where rendering bill provider is not present, the billing provider is assumed to be the rendering provider for all services on this bill. If the billing provider was not an individual, a jurisdiction may require a rendering bill provider to be specified. I use the state license number from Texas Physicians Registry Data and license number reported for billing provider or rendering bill provider from Texas Workers' Compensation Medical Claims Data to match physicians. Among claims with physicians who are licensed in Texas and have Doctor of Medicine (MD) degrees, 85% of claims are successfully matched to the Texas Physicians Registry Data.

Official Disability Guidelines (ODG) Data

Official Disability Guidelines (ODG) provides medical treatment guidelines and return-to-work guidelines for conditions commonly associated with the workplace illness or injuries. ODG is designed for clinical practice as well as utilization review/management. To facilitate our understanding of medical coding and treatment for various injuries, I use the treatment guidelines and Crosswalk UR Advisor from ODG to obtain information on recommended medical treatment, auto-approved medical services and statistics on costs, duration of treatment, and day away from work.

A.2 Medical Procedure Codes

Definition of types of procedures

I follow the CPT Standard codebook to classify CPT (HCPCS level I) codes. Surgical medical services are defined as CPT codes from 10021 to 69990. The types of medical services in section 1.5.3 is defined as follows:

- Integumentary System: 10040 - 19499
- Musculoskeletal System: 20000 - 29999
- Cardiovascular System: 33010 - 39599
- Digestive System: 40490 - 49999
- Nervous System: 61000 - 64999
- Evaluation and Management: 99201 - 99499
- Anesthesia: 00100 - 01999 99100 - 99150
- Radiology: 70000 - 79999
- Pathology and Laboratory: 80000 - 89398
- Medicine: 90281 - 99099 99151 - 99199 99500 - 99607
- Device and Equipment: HCPCS Level II

Definition of discretionary procedures

Following Card et al. (2009), I performed a t-test of equality of likelihood of weekend and weekday visits for different medical procedures. If medical procedures are not deferrable, it is more likely that the t-statistics would be insignificant. On the other hand, for discretionary medical procedures, it is less likely to be done during weekdays. I classify the medical procedures with t-statistics above the median in the distribution as elective medical procedures, which are grouped by BETOS codes and listed below.

- P1F: Major Procedure - Explor/Decompr/Excisdisc

- P1G: Major Procedure - Other
- P2F: Major Procedure, Cardiovascular - Other
- P3D: Major Procedure, Orthopedic - Other
- P5A: Ambulatory Procedures - Skin
- P5B: Ambulatory Procedures - Musculoskeletal
- P5E: Ambulatory Procedures - Other
- P6A: Minor Procedures - Skin
- P6B: Minor Procedures - Musculoskeletal
- P6C: Minor Procedures - Other
- P8A: Endoscopy - Arthroscopy
- I1F: Standard Imaging - Other
- I4B: Imaging/Procedure - Other
- T1A: Lab Tests - Routine Venipuncture

An alternative definition of discretionary procedures is using the classification from Medicare Part B data. I convert HCPCS codes to BETOS codes using a crosswalk available from CMS, and follow the categorization used by Clemens and Gottlieb (2014) to determine which procedures are for less discretionary care. Specifically, I define elective procedures as claims associated with the following BETOS codes:

- P2A: Major procedure, cardiovascular - CABG
- P2C: Major Procedure, cardiovascular - Thromboendarterectomy
- P2D: Major procedure, cardiovascular - Coronary angioplasty (PTCA)
- P3B: Major procedure, orthopedic - Hip replacement
- P3C: Major procedure, orthopedic - Knee replacement

- P4B: Eye procedure - cataract removal/lens insertion
- P5A: Ambulatory procedures - skin
- P5B: Ambulatory procedures - musculoskeletal
- P6A: Minor procedures - skin
- P6B: Minor procedures - musculoskeletal
- P8A: Endoscopy - arthroscopy
- P8B: Endoscopy - upper gastrointestinal
- P8C: Endoscopy - sigmoidoscopy
- P8D: Endoscopy - colonoscopy
- P8E: Endoscopy - cystoscopy
- P8F: Endoscopy - bronchoscopy
- P8G: Endoscopy - laparoscopic cholecystectomy
- P8H: Endoscopy - laryngoscopy
- I4A: Imaging/procedure - heart including cardiac catheter

When exploring whether the response in quantity is more pronounced for elective surgical services, using definition of elective procedures from Clemens and Gottlieb (2014), figure A.4 shows the effect on quantity for elective surgical services. The estimates are close to the baseline results with slightly larger magnitude from 2010 to 2012, though not significantly different from the baseline estimates.

A.3 Details on Workers' Compensation in Texas

According to the Survey of Employer Participation in the Texas Workers' Compensation System conducted by the Workers' Compensation Research Center and the

Public Policy Research Institute (PPRI) at Texas A&M University, 67% of Texas employers participated in the Texas Workers' Compensation program in 2012, covering 83% of Texas workers. Large employers are more likely to be "subscribers", with a participation rate around 83% in 2012. It is estimated that 75% of employees employed by non-subscribers are covered by non-subscriber alternative occupational benefit plans that pay medical and/or wage benefits to injured employees.

According to the Oregon Workers' Compensation Premium Rate Ranking reports, premium rates in Texas has a similar trend as the national average premium rates, and are about 15% higher than the national average from 2004 to 2010. There has been across-the-board reductions in reluctivities regulated by TDI during the time period studied. However, these changes in premiums applies to all employers in all industries and locations and should be independent of the medical care received by injured workers.

According to the Survey of Occupational Injuries and Illnesses (SOII) conducted by the U.S. Bureau of Labor Statistics, the incidence of nonfatal injuries in Texas has a similar trend as the national statistics, as shown in figure A.3, with declining incidence of injuries over time.

Similarity between Worker's Compensation patients and patients covered by health insurance

One might be worried that the medical conditions and treatment Worker's Compensation patients are different from those covered by health insurance, such as employer-sponsored health insurance, Medicaid or Medicare. If so, the generalizability of empirical results in this paper would be limited. To address this concern, using the top 30 medical conditions for patients from the Medical Expenditure Panel Survey (MEPS), I listed the medical conditions that are also popular for Worker's Compensation patients below.

- Mental disorders
- Osteoarthritis and other non-traumatic joint disorders
- Back problems
- Trauma-related disorders
- Chronic obstructive pulmonary disease and asthma
- eHypertension
- Heart conditions
- Hyperlipidemia
- Skin disorders
- Other care and screening
- Acute bronchitis and upper respiratory infection
- Other bone and musculoskeletal disease
- Thyroid disease
- Headache

A.4 Additional Analysis

A.4.1 Additional Robustness Checks

Following Campolieti and Hyatt (2006) and Card and McCall (1996), I group patients' main diagnosis into three categories using ICD-9 diagnosis codes: (1) Strains or Sprains, (2) Non-Sprains, and (3) Occupational Diseases, and estimate the same specification separately for the three categories. Results are shown in table A.2. The estimates are roughly the same across these three types of diagnosis.

In addition to the analysis complementariness between surgical and nonsurgical services, table A.1 shows the estimated effects for those are less likely to be complementary to surgical services. Column (1) uses a subsample of nonsurgical services with certain surgical services during course of treatment for the same patients, same as figure 1.10 (a). In comparison, column (2) uses a subsample of nonsurgical services without any surgical services during course of treatment for the same patients. Column (3) uses nonsurgical services that are performed within 20 days of certain surgical services, same as figure 1.10 (b). Column (4) uses nonsurgical services that are performed more than 20 days of certain surgical services. See text in section 1.5.2 for more details.

A.4.2 Analysis on Referrals

Referrals are an important part of healthcare, while little is know about whether payments impact referrals. Taking advantage of the policy change in reimbursement rate for WC claims, I examine the change in referrals in different types of healthcare management systems.

TDI encourages participation in healthcare networks to increase access for workers and lower costs. Healthcare networks started in 2006, and has been steadily expanding over time. For Workers' Compensation claims, the primary care physician who first initiates the treatment for covered workers would serve as the gate-keeper doctor and monitor the course of treatment to contain cost. All referrals to specialists have to be made by the gate-keeper doctor. The increase in reimbursement rate for surgical services impact mostly people with surgical specialties, who would have the possibility to perform some kind of surgical services. It is possible that physicians in the same network could share any additional payment together. As a result, a primary care physician in healthcare networks could be incentivized to give out more referrals to specialists within the same network.

Here I analyze whether primary care physicians in the healthcare networks are more likely to give referrals to specialities after the increase in reimbursement, compared to primary care physicians not in network.

To answer this question, I estimate the following specification in equation A.1 following a difference-in-difference framework, using interaction terms between network status and year indicators and at the same time controlling for the main effects.

$$Y_{it} = \sum_{t \neq 2007} \beta_t \mathbb{1}_t Nework_i + \alpha_t \mathbb{1}_t + \theta Network_i + \alpha X_{it} + \theta Interim_t + \epsilon_{it} \qquad \text{(A.1)}$$

where t is the index of time (measured by year), i is an index for individual worker, $Nework_i$ is an indicator for workers whose primary care physicians are in healthcare networks, α_t is the year fixed effects, and β_t is the set coefficients for interaction terms between network status and year dummies. Year 2007 is omitted.[2]

Figure A.5 plots the estimates for β_t, coefficients of the interaction terms. Averaging the estimated effects from 2010 to 2012, after policy change, the probability of visiting a specialist is 5.5 percentage points higher for providers in network than those

[2] Texas House Bill 7, which was passed in 2005, allowed the formation of workers' compensation healthcare networks. An healthcare network is an organization formed to provide healthcare services to injured employees. Year 2005 is excluded from this analysis, because TDI started to certify the healthcare networks from early 2006. As of February 1, 2012, there were 30 TDI-certified networks.

not in network (mean of dependent variable is 0.44), and share of visits to specialists is 4.2 percentage points higher for providers in network than those not in network (mean of dependent variable is 0.62). These estimates suggest that physicians in healthcare networks are more likely to refer patients to specialists after the increase in reimbursement for surgical services in a facility.

A.4.3 Analysis on Physicians Treating WC Patients

Increase in reimbursement rates could potentially attract more physicians to treat injured workers in Texas, thus improving access to care for workers. Recall that the increase in reimbursement rates only applies to surgical services performed in facility settings. The increase in reimbursement mostly benefits physicians with a surgical speciality, who are able to perform surgical services. As confirmed by medical claims data, the majority of surgical services are performed by physicians with surgical specialities.[3] In this section, I examine whether the increase in reimbursement rates for surgical services induce more participation from providers with surgical specialities in Workers' Compensation system.[4]

First, I aggregate physicians who have treated patients in the Texas Workers' Compensation system to the specialty and year level. For each specialty, I assign an indicator,

[3] Examples of surgical specialities includes general surgery, orthopedic surgery, neurological surgery, cardiovascular surgery, and thoracic surgery. Surgical services account for about on average 23.31% of total services provided by physicians with surgical specialties, while only 5% for physicians with other specialties.

[4] In an ideal case, one would measure participation as physicians' intention to treat patients on worker compensation benefits. However, due to data limitation, here participation is measured as the actual treatment of injured workers, as observed in claims data. As patients from Workers' Compensation is a small fraction of the overall pool of potential patients for physicians, this measure is limited. The results presented here for provider level analysis should be interpreted with this caveat in mind.

which equals to one if the specialty is related to performing surgeries.[5] Then I estimate a specification in equation A.2 with interactions terms between year indicators and surgical speciality indicators using the aggregated data at speciality and year level. I look at outcomes such as the total number of physicians, the total number of claims and the total or average amount paid to physicians.

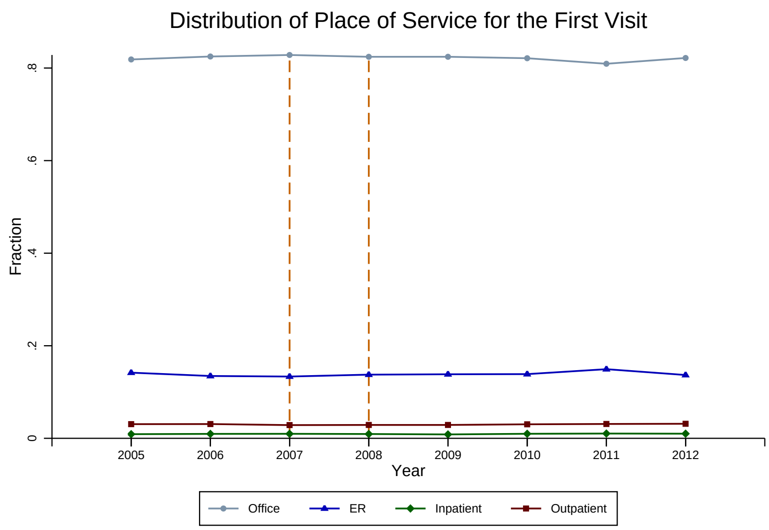
$$Y_{st} = \sum_{t \neq 2007} \beta_t \mathbb{1}_t SurgicalSpeciality_s + \alpha_t \mathbb{1}_t + \theta_s \mathbb{1}_s + \epsilon_{st} \tag{A.2}$$

where t is the index of time (measured by year), s represents physicians' specialty, $SurgicalSpeciality_s$ is an indicator for surgical specialty, θ_s are specialty fixed effects, α_t is the year fixed effects, and β_t is the set coefficients for interaction terms between surgical specialty dummy and year dummies. Year 2007 is the omitted category.

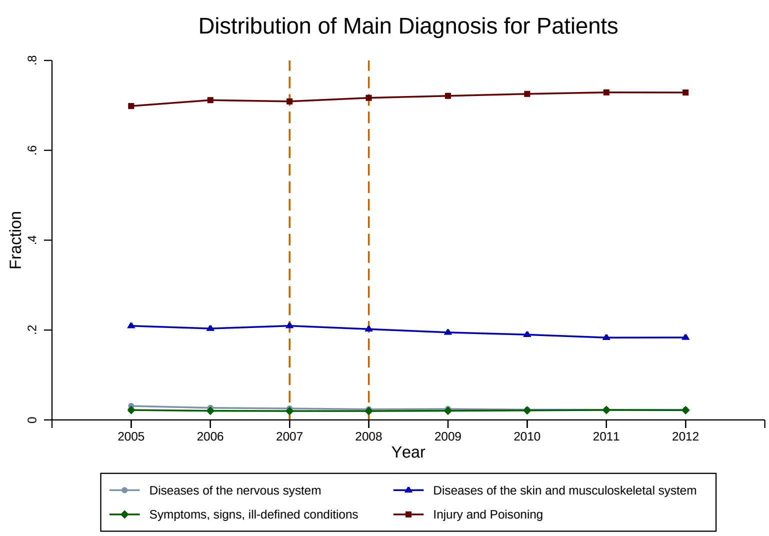
Results from this set of analysis is in table A.3. After the policy change in early 2008, we observe an increase of 17% to 32% in total number of physicians in surgical specialty, compared with total number of physicians in other specialties (in table A.3 column 1). The supply of physicians is unlikely to be affected by the change in reimbursement rates. The estimates indicate that more physicians with surgical specialty treated injured workers, due to the increase in reimbursement rates for surgical services. In addition, the total number of claims, the total amount paid and the average amount paid also increased after 2008 for physicians with surgical specialties.

[5] In the physician registry data from Texas Medical Board, physicians could report a secondary specialty in addition to their primary specialty. If either the primary specialty or the secondary specialty involves performing surgeries, I code the surgical specialty indicator as one.

Figure A.1



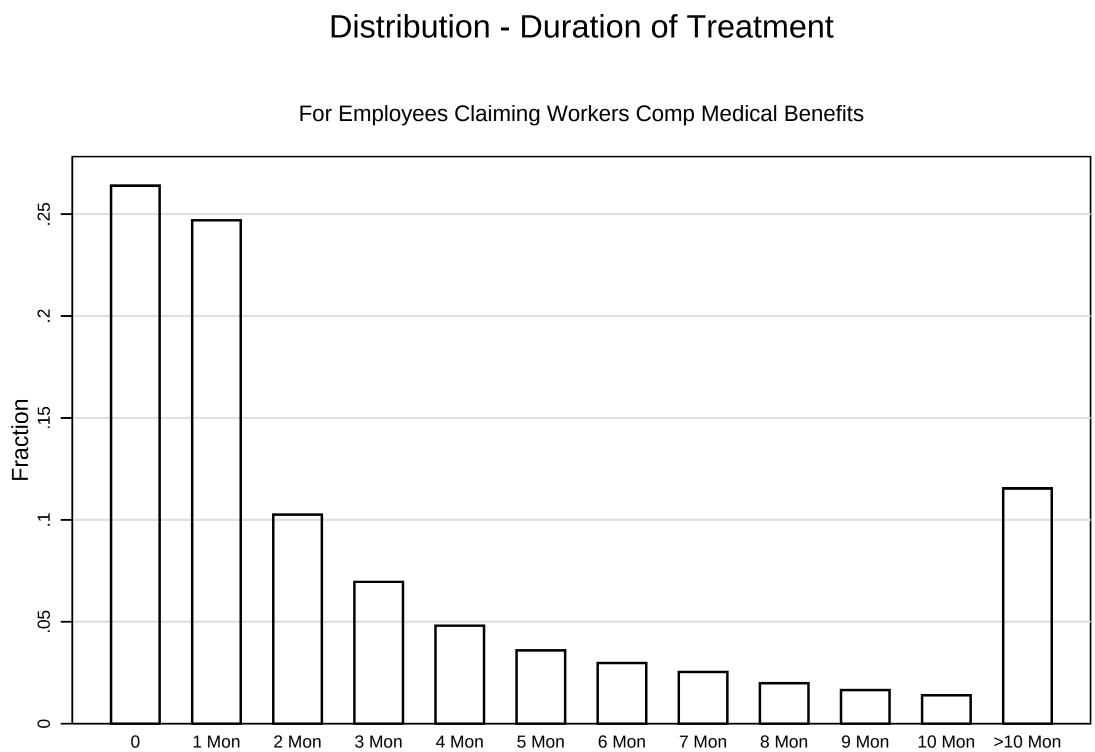
(a)



(b)

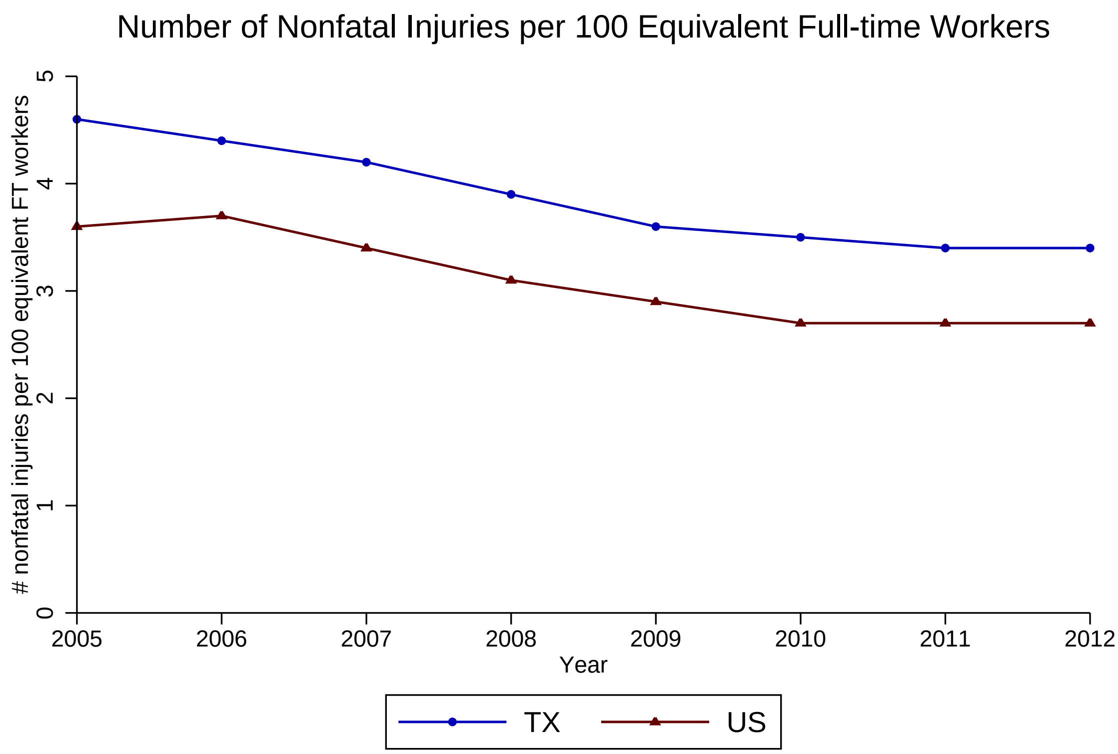
Notes: Figure (a) shows the distribution of place of service for injured workers' first claim. Figure (b) shows the distribution of diagnosis for injured workers' first claim.

Figure A.2



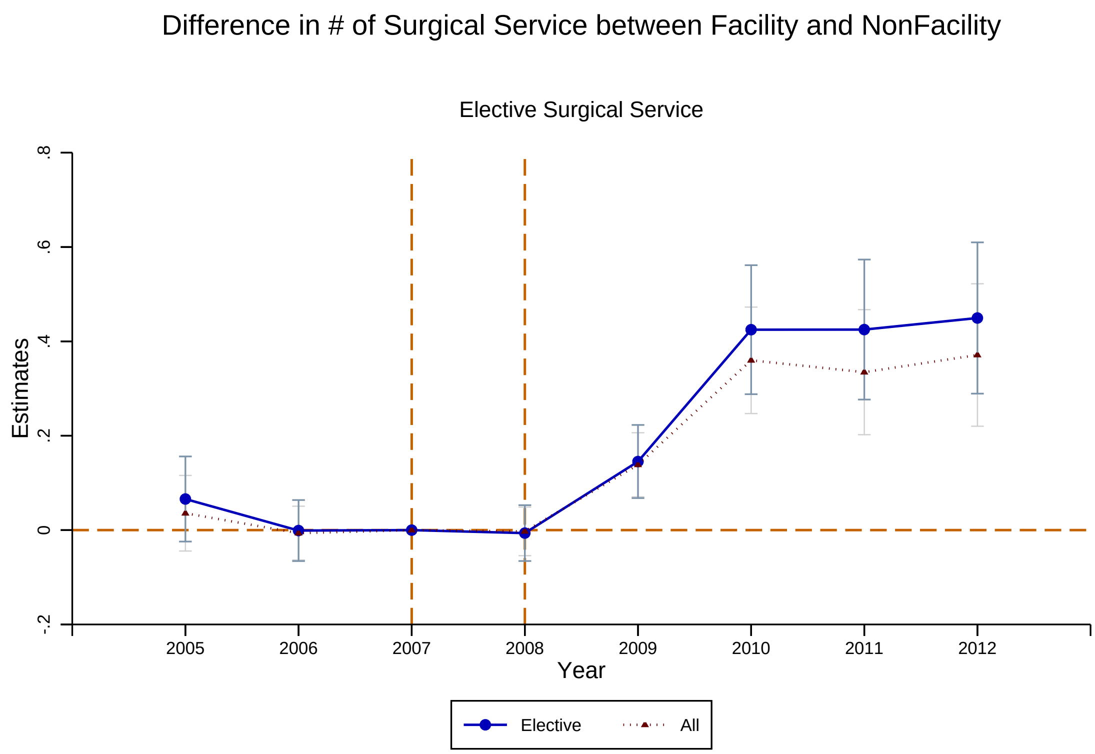
Notes: This figure shows the distribution of duration of treatment for injured workers. To minimize the possibility of truncation, employees with first claims in 2005 and 2012 are excluded, and employees with last claims later than 2012/6/30 are excluded as well. Total number of employees included for this figure is 1,535,815. Median of duration is about 26 days, and mean is 124 days. The 95th percentile is 582 days.

Figure A.3



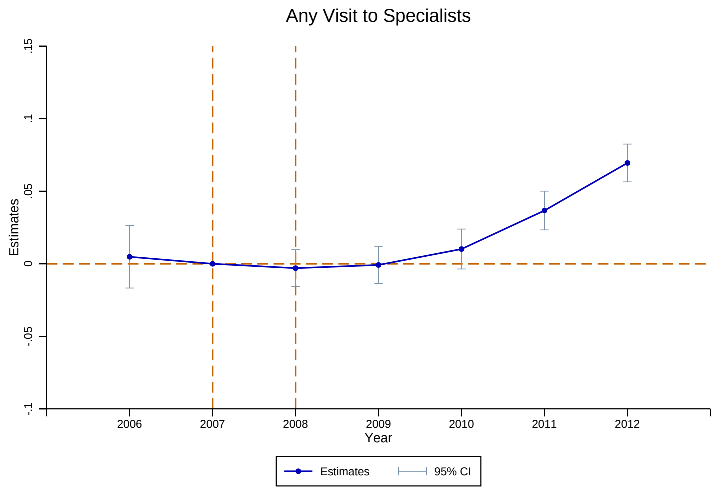
Notes: This figure shows the incidence of nonfatal injuries per 100 equivalent full-time workers. Data is from the Survey of Occupational Injuries and Illnesses (SOII) conducted by the U.S. Bureau of Labor Statistics.

Figure A.4

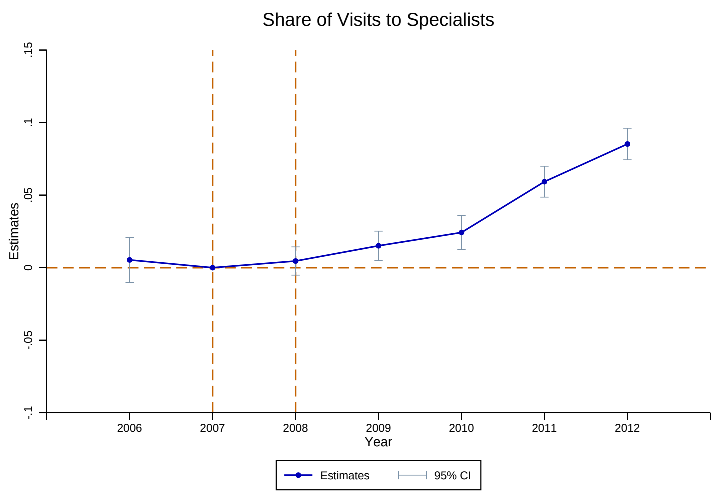


Notes: This figure plots the estimates of β_t from equation 1.4. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the total number of surgical services (in log) for a subsample of elective procedures. The estimates show the differences over time in total number of procedures between surgical services performed in facility and those in nonfacility settings. Definition of elective procedures follows Clemens and Gottlieb (2014), including BETOS codes P2A, P2C, P2D, P3B, P3C, P4B, P5A, P5B, P6A, P6B, P8A to P8H, and I4A. Elective surgical services are mostly major orthopedic procedures, ambulatory procedures, minor skin or musculoskeletal procedures, and endoscopy. See text in the appendix for details.

Figure A.5



(a)



(b)

Notes: This figure plots the estimates of β_t from equation A.1. Data is aggregated to the patient level from Texas Workers' Compensation medical claims data from 2005 to 2012. Year is based on the date of a worker's first claim. To ensure the accurate coding of date of first claims, employees with first claims from January 1, 2005 to March 31, 2005 are excluded. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at county level based on employees' places of residence. This set of figure show differences in referrals between workers treated by physicians in healthcare networks and workers treated by physicians not in healthcare networker.

Table A.1: Total Quantity of Surgical Services (subset)

	Log of Number of Non-Surgical Services			
	(1)	(2)	(3)	(4)
Facility*Y2005	0.025	-0.030	0.045	-0.074
	(0.034)	(0.039)	(0.038)	(0.163)
Facility*Y2006	0.012	-0.015	-0.020	-0.025
	(0.021)	(0.022)	(0.023)	(0.093)
Facility*Y2008	0.005	0.029	-0.008	-0.067
	(0.020)	(0.025)	(0.022)	(0.098)
Facility*Y2009	0.055**	0.031	0.059*	-0.156
	(0.026)	(0.031)	(0.030)	(0.101)
Facility*Y2010	0.178***	0.088**	0.185***	-0.100
	(0.035)	(0.040)	(0.044)	(0.116)
Facility*Y2011	0.210***	0.101**	0.184***	-0.042
	(0.042)	(0.048)	(0.058)	(0.132)
Facility*Y2012	0.189***	0.092*	0.173***	0.024
	(0.049)	(0.055)	(0.062)	(0.176)
Year FE	X	X	X	X
Service FE	X	X	X	X
Facility FE	X	X	X	X
N	6184	5432	4320	960
Mean of Dep. Var	5.12	5.07	5.31	4.70

Note: This table shows the estimates of β_t from equation 1.4 using subsamples of nonsurgical services defined below. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. The outcome variable is the total number of nonsurgical services (in log). The estimates show the differences over time in total number of procedures between nonsurgical services performed in facility and those in nonfacility settings. This set of figures explore the complementariness between surgical and nonsurgical services. Column (1) uses a subsample of nonsurgical services with certain surgical services during course of treatment for the same patients, same as figure 1.10 (a). In comparison, column (2) uses a subsample of nonsurgical services without any surgical services during course of treatment for the same patients. Column (3) uses nonsurgical services that are performed within 20 days of certain surgical services, same as figure 1.10 (b). Column (4) uses nonsurgical services that are performed more than 20 days of certain surgical services. See text in section 1.5.2 for more details. This set of estimates is to show nonsurgical services which are related to surgical services have spillover effects from the increase in payment for surgical services. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table A.2: Effect on Payment and Quantity by Diagnosis

	Strains or Sprains		**Non-Sprains**		**Occupational Diseases**	
	Log of Avg Payment	Log of Num of Services	Log of Avg Payment	Log of Num of Services	Log of Avg Payment	Log of Num of Services
Facility*Y2005	0.001	0.076	0.015	0.044	-0.000	0.038
	(0.069)	(0.105)	(0.027)	(0.037)	(0.036)	(0.048)
Facility*Y2006	-0.050	0.037	-0.025	0.029	-0.062*	0.057
	(0.065)	(0.082)	(0.030)	(0.039)	(0.034)	(0.045)
Facility*Y2008	0.106	-0.071	0.092***	0.086**	0.027	0.077
	(0.085)	(0.131)	(0.030)	(0.043)	(0.036)	(0.048)
Facility*Y2009	0.298***	0.130	0.130***	0.324***	0.130***	0.218***
	(0.076)	(0.134)	(0.034)	(0.043)	(0.044)	(0.054)
Facility*Y2010	0.264***	0.452***	0.145***	0.458***	0.185***	0.524***
	(0.096)	(0.138)	(0.032)	(0.053)	(0.051)	(0.072)
Facility*Y2011	0.119	0.398***	0.135***	0.431***	0.142***	0.505***
	(0.080)	(0.149)	(0.037)	(0.057)	(0.050)	(0.077)
Facility*Y2012	0.221**	0.422***	0.166***	0.437***	0.203***	0.495***
	(0.088)	(0.154)	(0.039)	(0.053)	(0.053)	(0.090)
Year FE	X	X	X	X	X	X
Service FE	X	X	X	X	X	X
Facility FE	X	X	X	X	X	X
N	608	608	2544	2544	2624	2624
Mean of Dep. Var.	6.03	2.68	6.28	2.60	6.38	2.83

Note: This table shows the estimates of interaction terms of β_t from equation 1.4, for three subsamples based on ICD-9 diagnosis codes. Data is aggregated to the service-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at the service level. This table reports estimates for log of average payment and log of total number of procedures for surgical services. Non-sprain injuries include burns, lacerations, and crushing wounds. The occupational disease category includes carpal tunnel syndrome and herniated disc problems. This classification is adapted from Campolieti and Hyatt (2006) and Card and McCall (1996). Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table A.3: Changes on the Number of Physicians and the Claims/Payment per Physician

	Log(#Physicians)	Log(#Claims)	Log(Total Paid)	Log(Avg Paid)
SurgicalSpecialty*Y2005	0.091	0.289	0.131	0.013
	(0.082)	(0.190)	(0.285)	(0.304)
SurgicalSpecialty*Y2006	0.071	0.200	-0.011	-0.103
	(0.070)	(0.165)	(0.370)	(0.362)
SurgicalSpecialty*Y2008	0.125*	0.592***	0.573**	0.401
	(0.070)	(0.181)	(0.257)	(0.284)
SurgicalSpecialty*Y2009	0.168**	0.528**	0.735**	0.525*
	(0.083)	(0.219)	(0.289)	(0.298)
SurgicalSpecialty*Y2010	0.242**	0.629***	0.786***	0.473*
	(0.096)	(0.229)	(0.265)	(0.255)
SurgicalSpecialty*Y2011	0.311***	0.835***	0.979***	0.566*
	(0.096)	(0.258)	(0.325)	(0.307)
SurgicalSpecialty*Y2012	0.306***	0.706***	0.759*	0.375
	(0.107)	(0.252)	(0.395)	(0.358)
Year FE	X	X	X	X
Specialty FE	X	X	X	X
N	1384	1384	1384	1384
Mean of Dep. Var.	2.92	5.53	10.64	7.90

Note: This table shows the estimates of β_t from equation A.2. Data is aggregated to physicians' specialty-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at specialty level. Specialty is reported for each physician in the physician registry from Texas Medical Board. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table A.4: Changes on the Number of Physicians and the Claims/Payment per Physician

	Log(# Physicians)	Log(# Claims)	Log(Total Paid)	Log(Avg Paid)
SurgicalSpecialty*Y2005	0.086	0.285	0.127	0.014
	(0.081)	(0.191)	(0.287)	(0.305)
SurgicalSpecialty*Y2006	0.067	0.197	-0.014	-0.102
	(0.070)	(0.165)	(0.371)	(0.363)
SurgicalSpecialty*Y2008	0.127*	0.593***	0.575**	0.401
	(0.070)	(0.181)	(0.257)	(0.284)
SurgicalSpecialty*Y2009	0.172**	0.532**	0.738**	0.525*
	(0.083)	(0.219)	(0.289)	(0.297)
SurgicalSpecialty*Y2010	0.249**	0.634***	0.791***	0.471*
	(0.096)	(0.229)	(0.265)	(0.255)
SurgicalSpecialty*Y2011	0.321***	0.842***	0.986***	0.564*
	(0.095)	(0.258)	(0.326)	(0.307)
SurgicalSpecialty*Y2012	0.319***	0.715***	0.768*	0.373
	(0.107)	(0.253)	(0.395)	(0.358)
Total # by Specialty	X	X	X	X
Year FE	X	X	X	X
Specialty FE	X	X	X	X
N	1384	1384	1384	1384
Mean of Dep. Var.	2.92	5.53	10.65	7.90

Note: This table shows the estimates of β_t from equation A.2, with an additional control variable for total number of physicians by speciality. Data is aggregated to physicians' specialty-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at specialty level. Specialty is reported for each physician in the physician registry from Texas Medical Board. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Table A.5: Changes on the Number of Physicians by Group

	Log of Number of Physicians	
	Existing	New
SurgicalSpecialty*Y2005	0.207	0.142
	(0.352)	(0.125)
SurgicalSpecialty*Y2006	-0.065	0.126
	(0.089)	(0.104)
SurgicalSpecialty*Y2008	-0.013	0.162
	(0.081)	(0.100)
SurgicalSpecialty*Y2009	0.075	0.145
	(0.099)	(0.104)
SurgicalSpecialty*Y2010	0.094	0.372***
	(0.096)	(0.119)
SurgicalSpecialty*Y2011	0.203*	0.295***
	(0.111)	(0.113)
SurgicalSpecialty*Y2012	0.275**	0.224*
	(0.115)	(0.121)
Total # by Specialty	X	X
Year FE	X	X
Specialty FE	X	X
N	1384	1384
Mean of Dep. Var.	2.30	1.92

Note: This table shows the estimates of β_t from equation A.2 using total number of physicians as the outcome variable, separately for existing physicians and new physicians. Data is aggregated to physicians' specialty-year level from Texas Workers' Compensation medical claims data from 2005 to 2012. β_{2007} is the benchmark and is set to zero. The increase in maximum reimbursement rates took effect on March 1, 2008. Robust standard errors are clustered at specialty level. Specialty is reported for each physician in the physician registry from Texas Medical Board. This table shows that number of physicians increased more after 2008 from entry of physicians who have never treated Workers' Compensation patients before. Standard errors in parentheses. * p <0.10 , ** p <0.05, *** p <0.01

Appendix B

Appendix: Cash-on-Hand and Demand for Credit

B.1 Additional Analysis

Reduced Form Analysis

I present the reduced form analysis as stated in equation 2.3 in table B.4. I present the results on loan applications first. As EITC top-up rates increases by 10%, the number of borrowers decreased by 6.3%, and the number of loan applications decreased by 8.1%. For originated loans, number of borrowers with funded loans decreased by 7.1%, similar to the loan application results although the the estimate is insignificant. This is likely due to the reduced sample size in the originated loan data set, as the majority of loan applications are denied or unfunded by lenders.

Cross-county Distribution of EITC benefits and Loan Applications

Figure B.1 shows the distribution of loan applications and the amount of EITC benefits received across counties. Figure (a) shows the fraction of borrowers I observed in loan-level data among the county-level population by decile, with the darker colors indicating higher fractions. Figure (b) shows the actual amount of EITC benefits received at county level by decile, with the darker colors indicating higher amounts. Comparing these two figures, we can see that higher EITC benefits and a higher density of borrowers are located in southern and western areas, which could be due to common local characteristics or economic shocks.[1]

Additional Checks on Balance of Characteristics across State Borders

In table B.1 and table B.2, I present additional checks on the balance of characteristics across state borders. Other than the demographic and socioeconomic characteristics, regulations in the small dollar credit market could be different across states as well. I ran a similar specification using payday loan regulation as outcomes. The first panel uses an indicator for the presence of regulations on loan size, interest rate, etc. The second panel focuses on the specific regulations, for example, the maximum loan size or interest rate allowed. The results in table B.1 show that the regulations are uncorrelated with the instrument, the generosity of state EITC benefits. Additionally, one might also be concerned that people in different states might have different tax filing behaviors or use of financial services. I also show in table B.2 that the use of direct deposit and refund anticipation loans (RAL) or refund anticipation checks (RAC) is balanced across borders in the same commuting zone.

Additional Placebo Analysis

I implemented an additional placebo check to ensure that the estimates presented in previous sections are valid. First, I constructed placebo state boundaries to verify the estimates are robust to omitted characteristics of geographical areas. Specifically, I divide

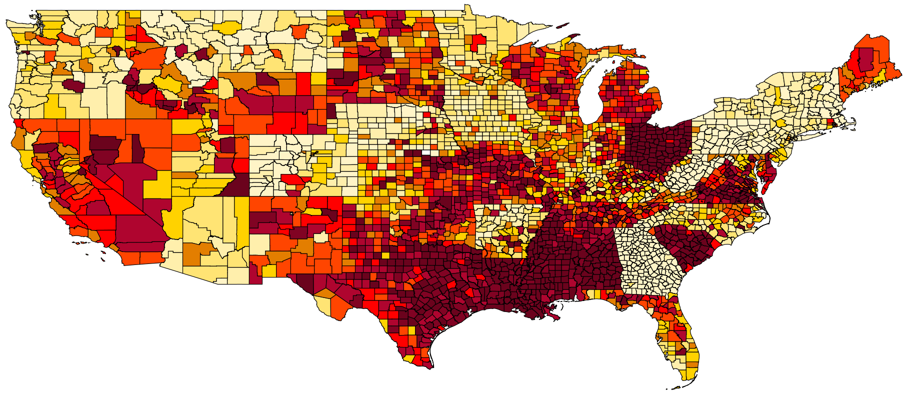
[1] Cutoffs for the deciles of average EITC benefits (in $) are 1906, 1990, 2057, 2132, 2164, 2194, 2231, 2306, and 2476. Cutoffs for the deciles of fraction of borrowers (in %) are .16, .29, .48, .66, .81, 1.06, 1.26, 1.80, and 2.56.

each CZ-state area in cross-border CZs into two pieces: the border area within 20 kilometers of the state boundary and the remainder of the CZ-state area not directly bordering the neighboring state. Thus the newly created “placebo boundary” is entirely inside the state. Using this “placebo boundary” as the state border, I assign the border area a counterfactual instrument (the simulated instrument for EITC benefits generosity) equal to that of neighboring state and keep the true value of the simulated instrument for the other area. Then I run the same specifications using this newly created instrument and control for CZ-state fixed effects, instead of CZ fixed effects. The goal of this test is to show that the estimates are robust to omitted variables that could be trending geographically from one state to another. The results are reported in table B.3. As expected, estimates are insignificant, indicating that it is unlikely that other characterizes trending geographically confound the estimates.

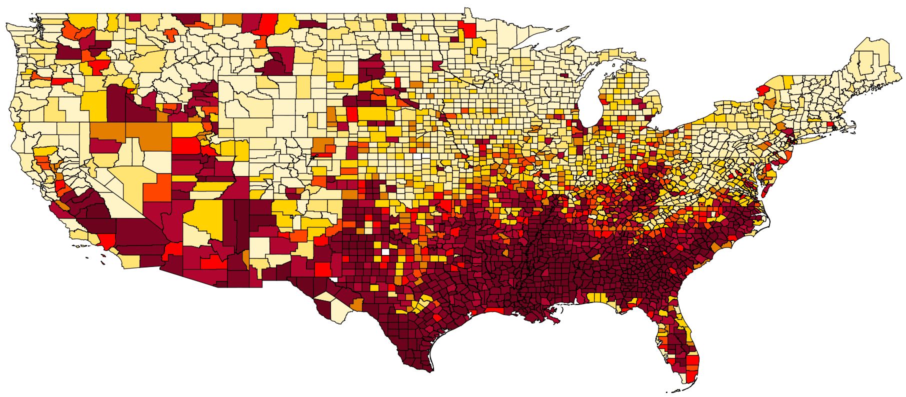
Additional Analysis on Default Rate

I look at the default rate among all originated loans for the offshore/tribal lenders. Offshore/tribal lenders on average have a higher default rate than state-licensed lenders (32.7% vs. 26.3%). Table B.6 shows that $100 additional EITC benefits reduce the default rate by 2.3 percentage points for offshore/tribal lenders. This is slightly higher than the effects on state-licensed lenders shown in the text.

Figure B.1



(a) Density of Borrowers across Counties



(b) Average EITC Benfits Received across Counties

Notes: Figure (a) shows the distribution of borrowers for small dollar loans across counties for year 2010 by decile, with darker color indicating more borrowers. Figure (b) shows the distribution of average amount of EITC benefits received across counties for year 2010 by decile, with darker color indicating higher average EITC benefits.

Table B.1: Check on Regulations on Payday Loans across State Borders

Balance in Regulations on Payday Loans				
	Coefficient of Log of Simulated IV			
Dep. Var.	Est.	Std. Err.	P-value	Mean of Dep. Var.
Any Regulation on				
Loan Size	-0.797	0.636	0.220	0.094
Interest Rate	0.394	0.923	0.672	0.219
Rollover	-0.888	1.072	0.414	0.625
Min Loan Term	-0.440	1.035	0.673	0.688
Max Loan Term	0.498	0.869	0.571	0.188
Regulation on				
Loan Size ($)	134.482	975.042	0.891	631.035
Interest Rate (APR)	-435.840	800.342	0.591	498.299
Min Loan Term (Days)	4.130	11.527	0.729	11.300
Max Loan Term (Days)	-0.641	41.975	0.988	39.000

Note: This table shows the coefficients of the simulated instrument from equation 2.3 on state level regulations on small dollar credit products such as payday loans. Data on regulations are from National Conference of State Legislatures (NCSL). The sample includes only zipcode areas in commuting zones that span state borders. Robust standard errors are clustered at the commuting zone level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.2: Check on EITC Eligibility and Tax Filing

Balance in EITC Eligibility and Tax Filing				
	Coefficient of Log of Simulated IV			
Dep. Var.	Est.	Std. Err.	P-value	Mean of Dep. Var.
Eligible for EITC	0.011	0.061	0.857	0.199
Used Direct Deposit	-0.004	0.056	0.949	0.774
Used Paid Tax Prep	0.029	0.063	0.649	0.577
Used RAL or RAC	0.005	0.003	0.131	0.289

Note: This table shows the coefficients of the simulated instrument from equation 2.3 on zip5 level outcomes, including fraction of the population being eligible for EITC, used direct deposit and used paid tax prepraration services. The sample includes only zipcode areas in commuting zones that span state borders. Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table B.3: Placebo Test

Effects of EITC on Loan Applications - Placebo Borders				
	#Borrowers	ln(#Borrower)	#Loans	ln(#Loans)
Avg EITC	-55.339	-0.906	-78.949	-0.920
	(62.085)	(0.854)	(92.557)	(0.878)
Mean of Dep. Var.	92.293	3.088	144.101	3.469
N	5089	5089	5089	5089
Total Population	X	X	X	X
Income Distributions	X	X	X	X
CZ-State FE	X	X	X	X
Census Region FE	X	X	X	X
Year FE	X	X	X	X

Note: This table shows the coefficients on average EITC (in $100) received using specification in equation 2.4, using $SimEITC_{st}$ as an instrument for $AvgEITC_{st}$. Placebo borders are completely within a state. CZ-state specific FE are included. See text for details. Data is the ZIP5-year level. This set of regression restricts to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table B.4: Reduced Form (Loan Applications)

Effects of EITC on Loan Applications - Reduced Form						
	#Borrowers			ln(#Borrower)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-8.886**	-7.200***	-4.168***	-0.122***	-0.122***	-0.063***
	(3.517)	(2.371)	(1.521)	(0.023)	(0.022)	(0.015)
Mean of Dep. Var.	109.648	107.49	81.80741	3.213837	3.174835	2.989484
	#Loans			ln(#Loans)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-15.779*	-12.341**	-7.873**	-0.138***	-0.143***	-0.081***
	(8.059)	(5.650)	(3.366)	(0.027)	(0.025)	(0.020)
Mean of Dep. Var.	167.5534	166.0037	127.4655	3.597145	3.556829	3.361337
N	1818	3241	6750	1818	3241	6750
Total Population	X	X	X	X	X	X
Income Distribution	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows coefficients on average EITC (in $100) received using specification in equation 2.4, without instrumenting $AvgEITC_{st}$ using $SimEITC_{st}$.The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table B.5: Reduced Form (Originated Loans)

Effects of EITC on Originated Loans - Reduced Form						
	#Borrowers			ln(#Borrower)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	-1.445***	-1.776***	-1.257**	-0.081*	-0.098**	-0.071
	(0.265)	(0.355)	(0.500)	(0.042)	(0.037)	(0.043)
Mean of Dep. Var.	15.625	15.210	11.367	2.133	2.078	1.826
	#Loans			ln(#Loans)		
	10 km	20 km	all	10 km	20 km	all
Avg EITC	5.021**	3.106	3.326	0.019	-0.022	0.011
	(1.942)	(2.296)	(2.765)	(0.066)	(0.065)	(0.073)
Mean of Dep. Var.	11.258	14.499	14.365	1.886	2.071	2.076
N	646	1127	2016	646	1127	2016
Total Population	X	X	X	X	X	X
Income Distributions	X	X	X	X	X	X
CZ FE	X	X	X	X	X	X
Census Region FE	X	X	X	X	X	X
Year FE	X	X	X	X	X	X

Note: This table shows coefficients on average EITC (in $100) received using specification in equation 2.4, without instrumenting $AvgEITC_{st}$ using $SimEITC_{st}$.The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Table B.6: IV Estimates (Default Rate for Offshore/Tribal Lenders)

Effects of EITC on Default Rate - IV Estimates			
	offshore/tribal lenders		
	10 km	20 km	all
Avg EITC	-0.012*	-0.021***	-0.023***
	(0.007)	(0.005)	(0.004)
Mean of Dep. Var.	0.336	0.336	0.327
N	1618	2840	5878
Total Population	X	X	X
Income Distribution	X	X	X
CZ FE	X	X	X
Census Region FE	X	X	X
Year FE	X	X	X

Note: This table shows coefficients on average EITC (in $100) received using specification in equation 2.4, without instrumenting $AvgEITC_{st}$ using $SimEITC_{st}$. The column named "all" includes all ZIP5 areas in the same commuting zones that span state borders. The column named "10 km" is restricted to to ZIP5 areas within 10 km of state borders, and the column named "20 km" is restricted to to ZIP5 areas within 20 km of state borders. Data is the ZIP5-year level. This set of regression is restricted to states that allow payday loans and state-licensed lenders. States with nonrefundable state EITC are excluded (DE, ME and VA). Robust standard errors are clustered at the commuting zone level. * p <0.10 , ** p <0.05, *** p <0.01

Bibliography

Daniel Aaronson, Sumit Agarwal, and Eric French. The spending and debt response to minimum wage hikes. *American Economic Review*, 102(7):3111–39, 2012. doi: 10.1257/aer.102.7.3111. URL http://www.aeaweb.org/articles.php?doi=10.1257/aer.102.7.3111.

Robert Argento Ackerman, Gerhard Fries, and Richard A Windle. Changes in us family finances from 2007 to 2010: Evidence from the survey of consumer finances. *Federal Reserve Bulletin*, 100:1–80, 2012.

Sumit Agarwal, Liu Chunlin, and Nicholas S Souleles. The reaction of consumer spending and debt to tax rebates-evidence from consumer credit data. *Journal of political economy*, 115(6):986–1019, 2007.

Laila Assanie, Mine Yücel, et al. Industry clusters shape texas economy. *Federal Reserve Bank of Dallas*, 2007.

Lisa Barrow and Leslie McGranahan. The effects of the earned income credit on the seasonality of household expenditures. *National Tax Journal*, 53(4):1211–44, 2000.

Marianne Bertrand and Adair Morse. What do high-interest borrowers do with their tax rebate? *The American Economic Review*, pages 418–423, 2009.

Zarek C. Brot-Goldberg, Amitabh Chandra, Benjamin R. Handel, and Jonathan T. Kolstad. What does a deductible do? the impact of cost-sharing on health care prices, quantities, and spending dynamics. Working Paper 21632, National Bureau of Economic Research, October 2015. URL http://www.nber.org/papers/w21632.

Marika Cabral and Mark Cullen. The effect of insurance coverage on preventive care. 2011.

Michele Campolieti and Douglas E Hyatt. Further evidence on the monday effect in workers' compensation. *Industrial & Labor Relations Review*, 59(3):438–450, 2006.

David Card and Brian P McCall. Is workers' compensation covering uninsured medical costs? evidence from the monday effect. *Industrial & Labor Relations Review*, 49(4): 690–706, 1996.

David Card, Carlos Dobkin, and Nicole Maestas. Does medicare save lives? *The Quarterly Journal of Economics*, 124(2):597–636, 2009.

Scott Carrell and Jonathan Zinman. In harms way? payday loan access and military personnel performance. *Federal Reserve Bank of Philadelphia*, 2008.

Amitabh Chandra, Jonathan Gruber, and Robin McKnight. Patient cost-sharing and hospitalization offsets in the elderly. *The American Economic Review*, 100(1):193, 2010.

Jeffrey Clemens and Joshua D Gottlieb. Do physicians' financial incentives affect medical treatment and patient health? *The American Economic Review*, 104(4):1320, 2014.

Dan Corro and John Robertson. The impact on physician reimbursement of changes to workers compensation medical fee schedules. *NCCI, March*, 2011.

Brahima Coulibaly and Geng Li. Do homeowners increase consumption after the last mortgage payment? an alternative test of the permanent income hypothesis. *Review of Economics and statistics*, 88(1):10–19, 2006.

Charles Courtemanche and Daifeng He. Tax incentives and the decision to purchase long-term care insurance. *Journal of Public Economics*, 93(1):296–310, 2009.

Janet Currie and Jonathan Gruber. Health insurance eligibility, utilization of medical care, and child health. *The Quarterly Journal of Economics*, 1996.

Gregory Elliehausen and Edward C Lawrence. Payday advance credit in america: An analysis of customer demand. *Credit Research Center, Georgetown University*, pages 39–40, 2001.

William N Evans and Timothy J Moore. Liquidity, economic activity, and mortality. *Review of Economics and Statistics*, 94(2):400–418, 2012.

Amy Finkelstein. The effect of tax subsidies to employer-provided supplementary health insurance: evidence from canada. *Journal of Public Economics*, 84(3):305 – 339, 2002. ISSN 0047-2727. doi: http://dx.doi.org/10.1016/S0047-2727(00)00155-9. URL http://www.sciencedirect.com/science/article/pii/S0047272700001559.

Price V Fishback and Shawn Everett Kantor. Did workers pay for the passage of workers' compensation laws? *The Quarterly Journal of Economics*, pages 713–742, 1995.

Elliott S Fisher, Julie P Bynum, and Jonathan S Skinner. Slowing the growth of health care costslessons from regional variation. *New England Journal of Medicine*, 360(9): 849–852, 2009.

Tal Gross and Jeremy Tobacman. Dangerous liquidity and the demand for health care evidence from the 2008 stimulus payments. *Journal of Human Resources*, 49(2):424–445, 2014.

Tal Gross, Matthew J Notowidigdo, and Jialan Wang. Liquidity constraints and consumer bankruptcy: Evidence from tax rebates. *Review of Economics and Statistics*, 96(3): 431–443, 2014.

Jonathan Gruber. The consumption smoothing benefits of unemployment insurance. *The American Economic Review*, pages 192–205, 1997.

Jonathan Gruber and Alan B Krueger. The incidence of mandated employer-provided insurance: Lessons from workers' compensation insurance. In *Tax Policy and the Economy, Volume 5*, pages 111–144. The MIT Press, 1991.

Jonathan Gruber and Michael Lettau. How elastic is the firms demand for health insurance? *Journal of Public Economics*, 88(7):1273–1293, 2004.

Jack Hadley and James D Reschovsky. Medicare fees and physicians medicare service volume: Beneficiaries treated and services per beneficiary. *International Journal of Health Care Finance and Economics*, 6(2):131–150, 2006.

Jack Hadley, Jean M Mitchell, and Jeanne Mandelblatt. Medicare fees and small area variations in breast-conserving surgery among elderly women. *Medical Care Research and Review*, 58(3):334–360, 2001.

Paul Heaton. The impact of health care reform on workers compensation medical care. 2012.

Steve Holt et al. Beyond lump sum periodic payment of the earned income tax credit. *Community Investments*, (Spr):26–31, 2009.

William C Hsiao, Peter Braun, Douwe Yntema, and Edmund R Becker. Estimating physicians' work for a resource-based relative-value scale. *New England Journal of Medicine*, 319(13):835–841, 1988.

Howard Jacob Karger. *Shortchanged: Life and debt in the fringe economy*. Berrett-Koehler Publishers, 2005.

Jonathan T. Kolstad and Amanda E. Kowalski. Mandate-based health reform and the labor market: Evidence from the massachusetts reform. *Journal of Health Economics*, 47:81 – 106, 2016. ISSN 0167-6296. doi: http://dx.doi.org/10.1016/j.jhealeco.2016.01.010. URL http://www.sciencedirect.com/science/article/pii/S0167629616000278.

Alan B Krueger. Incentive effects of workers' compensation insurance. *Journal of Public Economics*, 41(1):73–99, 1990a.

Alan B Krueger. Workers' compensation insurance and the duration of workplace injuries. Technical report, National Bureau of Economic Research, 1990b.

Sara LaLumia. The eitc, tax refunds, and unemployment spells. *American Economic Journal: Economic Policy*, 5(2):188–221, 2013.

Jonathan Lanning, Jesse Leary, Kathleen Burke, and Jialan Wang. Payday lending, cfpb data point. *Consumer Financial Protection Bureau*, 2014.

Dayanand S. Manoli and Nicholas Turner. Cash-on-hand & college enrollment: Evidence from population tax data and policy nonlinearities. Working Paper 19836, National Bureau of Economic Research, January 2014. URL http://www.nber.org/papers/w19836.

Thomas G McGuire and Mark V Pauly. Physician response to fee changes with multiple payers. *Journal of Health Economics*, 10(4):385–410, 1991.

MedPAC. Report to the congress: Medicare and the health care delivery system. 2013.

Brian T Melzer. The real costs of credit access: Evidence from the payday lending market. *The Quarterly Journal of Economics*, 126(1):517–555, 2011.

Bruce D Meyer, W Kip Viscusi, and David L Durbin. Workers' compensation and injury duration: evidence from a natural experiment. *The American economic review*, pages 322–340, 1995.

Katherine Michelmore. The effect of income on educational attainment: Evidence from state earned income tax credit expansions. *Available at SSRN 2356444*, 2013.

Jean M Mitchell, Jack Hadley, and Darrell J Gaskin. Physicians responses to medicare fee schedule reductions. *Medical Care*, 38(10):1029–1039, 2000.

Jonathan A Parker, Nicholas S Souleles, David S Johnson, and Robert McClelland. Consumer spending and the economic stimulus payments of 2008. *The American Economic Review*, 103(6):2530–2553, 2013.

Christopher A Parsons and Edward D Van Wesep. The timing of pay. *Journal of Financial Economics*, 109(2):373–397, 2013.

Pew. Payday lending in america: Who borrows, where they borrow, and why. *Pew Charitable Trusts Safe Small-Dollar Loans Research Project*, 2012.

Tomas J Philipson and Dana Goldman. Integrated insurance design in the presence of multiple medical technologies. *American Economic Review*, 97(2):427–432, 2007.

David Powell and Seth A Seabury. Medical care spending and labor market outcomes: Evidence from workers' compensation reforms. 2013.

Madelyn Schwartz Quattrone. Is the physician office the wild, wild west of health care? *The Journal of ambulatory care management*, 23(2):64–73, 2000.

Frank Schmid and Nathan Lord. The impact of physician fee schedule changes in workers compensation: Evidence from 31 states. 2012.

Ishita Sengupta, Virginia P Reno, and Marjorie L Baldwin. Workers compensation: Benefits, coverage, and costs, 2012. *National Academy of Social Insurance*, 2014.

Matthew D. Shapiro and Joel Slemrod. Consumer response to tax rebates. *American Economic Review*, 93(1):381–396, 2003. doi: 10.1257/000282803321455368.

URL http://www.aeaweb.org/articles.php?doi=10.1257/000282803321455368.

Michael A Stegman. Payday lending. *The Journal of Economic Perspectives*, pages 169–190, 2007.

Jennifer Sykes, Katrin Križ, Kathryn Edin, and Sarah Halpern-Meekin. Dignity and dreams what the earned income tax credit (eitc) means to low-income families. *American Sociological Review*, 80(2):243–267, 2015.

TDI. Health care cost and utilization in the texas workers compensation system 2000 -2013. Technical report, Texas Department of Insurance, Workers Compensation Research and Evaluation Group, 2014.

Barbara O. Wynn and Anne Boustead. *Home Health Care for California's Injured Workers*. RAND Corporation, 2015. URL http://www.jstor.org/stable/10.7249/j.ctt14bs2jg.

Barbara O Wynn, Leeh Hilborne, Peter Hussey, Elizabeth M Sloss, and Erin Murphy. Medicare payment differentials across ambulatory settings. 2008.

Barbara O. Wynn, John P. Caloyeras, and Nelson F. Soohoo. *Ambulatory Surgical Services Provided Under California Workers Compensation*. RAND Corporation, 2014. URL http://www.jstor.org/stable/10.7249/j.ctt6wq912.

Vita

Can Cui was born in Baoding, China. She attended Peking University where she earned a Bachelor of Arts in Economics and International Relations in 2010. In her third year of college, she attended the University of Hong Kong for a semester as an exchange student. She entered graduate study at the University of Texas at Austin Department of Economics in August, 2010. Her research focuses on the impact of financial incentive on healthcare providers, taxation policy, and demand in the small dollar credit market. She has also worked at RAND Corporation, Clarity Services Inc., and Capital One Auto Finance on policy research and statistical analysis.

This dissertation was typeset with LaTeX[†] by the author.

[†]LaTeX is a document preparation system developed by Leslie Lamport as a special version of Donald Knuth's TeX Program.