2017

The Effect Of Market Expansions On Provider Behavior In Dentistry

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The Effect Of Market Expansions On Provider Behavior In Dentistry

Abstract
How do market expansions that increase patient loads among offices affect provider treatment behavior? This question is immediately relevant to recent insurance expansions, where increases in insurance coverage may increase market demand for care. Because this may result in positive income shocks for providers, providers may alter how they treat patients across the entire practice to reallocate existing resources. Hence, a market expansion may not only impact treatment of new patients but also treatment of existing patients.

A simple extension of the McGuire and Pauly (1991) model predicts that an insurance expansion may be an effective policy lever not only to increase dental or medical utilization among populations prone to underutilization, but may also decrease provider-initiated overutilization among existing patients. I then substantiate what decreases in provider-initiated overutilization looks like using the clinical dental literature and reimbursement rates across procedures. The hypotheses generated by this model are then tested empirically using a novel source of dental claims data from Delta Dental of Michigan from 2008-2013. I leverage an exogenous increase in demand for provider services from a dependent coverage insurance expansion in the overall dental market. I use an instrumental variables strategy to isolate increases in patient load that come solely from dependent expansion, and isolate attention to continuously insured patients among dental practices to 1) remove any omitted factors influencing both practice intensity and patient load and 2) detect changes in treatment behavior initiated by providers, holding fixed demand-side factors. I find offices face up to a 8.64\% increase in office loads from the dependent expansion, which leads to substitution away from intensive cavity procedures towards routine procedures. These empirical results are consistent with the predictions of models of demand inducement and provider behavior. I then follow with a more detailed discussion of why demand inducement is an issue in the dental market and why an insurance expansion is only a partial solution. To conclude, I discuss the policy levers available for addressing the misalignment of clinical efficacy and provider reimbursement, using the theory of optimal insurance and optimal coverage of preventive care.

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Second Advisor
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THE EFFECT OF MARKET EXPANSIONS ON PROVIDER BEHAVIOR IN DENTISTRY

Shulamite S. Chiu

A DISSERTATION

in

Health Care Management and Economics

For the Graduate Group in Managerial Science and Applied Economics

Presented to the Faculties of the University of Pennsylvania

in

Partial Fulfillment of the Requirements for the

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THE EFFECT OF MARKET EXPANSIONS ON PROVIDER BEHAVIOR IN DENTISTRY

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Shulamite Sian Chiu

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I dedicate my dissertation work to all those who have cherished and nourished me in so many ways - my family, my friends, and my church family. I love you all.
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Shulamite Sian Huang

March 2017
ABSTRACT

THE EFFECT OF MARKET EXPANSIONS ON PROVIDER BEHAVIOR IN DENTISTRY

Shulamite S. Chiu

Daniel Polsky

How do market expansions that increase patient loads among offices affect provider treatment behavior? This question is immediately relevant to recent insurance expansions, where increases in insurance coverage may increase market demand for care. Because this may result in positive income shocks for providers, providers may alter how they treat patients across the entire practice to reallocate existing resources. Hence, a market expansion may not only impact treatment of new patients but also treatment of existing patients.

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CHAPTER 1: Introduction

How provider behavior responds to changes in financial incentives remains a central issue in health economics (McGuire, 2000; Arrow, 1963). In particular, if providers respond to changes in their financial incentives, whether they respond by decreasing their provision of low-value care when there is asymmetric information about the patient’s true health condition is still an outstanding question. The empirical literature in economics has generated mixed results, part of which is due to 1) lack of adequate claims or practice data that traces provider behavior across patients and insurers (Sintonen and Linnosmaa, 2000) and 2) the difficulty involved in finding an exogenous shock large enough to induce a change in provider decision-making (De Jaegher and Jegers, 2000).

The small but growing literature on the supply-side effects of insurance expansions has demonstrated that insurance expansions may provide a useful source of variation to examine how providers can alter supply-side behavior within their practices in response to sudden changes in their financial incentives, and has identified potential effects not only upon the population targeted by the insurance expansion, but upon entire practices. In particular, Buchmueller et al. (2016) showed that when state Medicaid programs added an adult dental benefit, dentists were able to increase participation in Medicaid and see more Medicaid patients without decreasing provision of visits to privately insured patients, with only a modest increase in the time spent working and modest increases in wait times. This was because dentists were able to use dental hygienists to provide routine procedures and could increase the use of dental hygienists. Along similar lines, Garthwaite (2012) found that office visits became shorter after implementation of the State Children’s Health Insurance (SCHIP) Program even as physicians increased their participation in the SCHIP program. These two studies examining the effect of public insurance expansions on provider behavior suggest overall that there may have been a change in the content of visits over all patients within practices (due to modest increases in wait times in Buchmueller et al. (2016) and shorter office visits in Garthwaite (2012) in response to each paper’s respective expansion.
of interest).

However, because the literature on the supply-side effects of insurance expansions has primarily examined survey data on providers and offices to look at how provider behavior and hiring decisions change in light of an insurance expansion, little is known about whether and how providers change the content of visits in order to respond to an insurance expansion. More concretely, it is unclear how changes in demand on the extensive margin may affect practice patterns on the intensive margin across patients within a practice.

The McGuire and Pauly (1991) model of provider behavior provides a theoretical foundation for thinking about how large demand shocks will affect provider treatment behavior. The original McGuire and Pauly (1991) model suggests that an exogenous decrease in patients within a practice provides a negative income shock to providers, who may exploit the informational asymmetry between providers and patients by increasing provision of high-intensity care that patients would not otherwise value with full information (demand inducement). This has been used most notably in Gruber and Owings (1996), where they tested an exogenous decline in demand stemming from declines in fertility over 1970-1982. They found that the negative income shock resulting from the decline in fertility was correlated with increases in cesarean utilization. The McGuire and Pauly (1991) model then also implies the opposite - if insurance expansions serve as a source of a positive income shock to offices, expansions may then lead to decreases in supplier-induced demand, if indeed supplier-induced demand is occurring.

I provide a few extensions to the McGuire and Pauly (1991) model in Section 2.1 to show how an exogenous increase in demand that comes from an insurance expansion may affect the incentive to induce demand for providers. Because the exogenous increase in demand comes from an insurance expansion, I differentiate continuously insured patients from new patients who may be facing changes in their demand for care due to changes in the out-of-pocket cost for treatment from the gain in insurance coverage. This predicts generally that though the predictions for how treatment intensity will change for the newly insured are
ambiguous, due to moral hazard effects operating in contrast to income effects, an insurance expansion will lead to a decline in treatment intensity for continuously insured patients who are fixed in any factors that influence demand for services. I also include a capacity constraint for practices to model how the incentive to induce demand will decline further if practices become capacity constrained, conditional on capacity-intensive treatments being exactly the high-intensity services that providers have financial incentive to induce for.

This paper is, to my knowledge, the first test of whether insurance expansions have an effect on supplier-induced demand. Previously, there were two primary difficulties in using insurance expansions as positive demand shocks: 1) insurance expansions may not translate directly to increases in access to care, and thus may not translate to demand shocks at the office-level; and 2) examining how provider behavior changes within visits requires claims-level data. In particular, Decker and Lipton (2015) hints at (1), suggesting that the effects of increases in coverage may have a larger effect on the use of dental care, and thereby the size of the demand shock to offices, if reimbursements to providers are higher in the case of Medicaid expansions. To ameliorate both issues of whether increases in coverage result in increased access and utilization and the existence of claims data to trace provider treatment behavior, I focus upon the dental care market, which faces the similar issues of physician agency as in the medical care market. Section 2.3 describes where the incentives to induce demand are in dentistry, and Chapter 3 discusses why insurance expansions in the dental market are likely to lead to large demand shocks at the office-level, and describes the claims-level data obtained from Delta Dental of Michigan, the main dental insurer in its geographic market. However, I give a brief preview in the following paragraphs to outline why the dental market is of interest in examining both the supply-side effects of insurance expansions and whether demand inducement occurs and to what extent.

Because dental care providers, like medical care providers, observe more information about the patient than the patient himself or the insurer, there is room for dental providers to induce demand without detection by both patients and insurers. An example of this is
dental procedures for cavities. A simple example of this arises in dentistry comes from one of the most common procedures - cavity fillings. Though a common and relatively simple procedure, reimbursements vary with the size of the filling, and X-rays typically do not capture the full extent of the tooth damage. Rather, the extent of the damage is known only when the dentist drills into the tooth, and due to the differences in reimbursement for simple versus more complex cavities, the dentist has an incentive to carry out the procedure for a larger filling than necessary. This can be done without penalty from the insurer or patient because there is no way to detect at a claim-by-claim level whether the dentist induced demand for a higher intensity procedure than would have otherwise been demanded by the consumer with perfect information. Inducement at an individual claim level is therefore neither observable nor verifiable.

A necessary question that follows then is whether the patient would care about an increase in intensity of (restorative) treatment given full information. In short, yes. One reason is that fillings do not last forever - they crack or degrade and must be replaced periodically. However, when fillings are replaced, the original hole does not suffice, but an increasingly larger hole in the tooth must be made with each consecutive filling replacement. The larger a hole is, the less the structural integrity of the tooth and the higher the risk of further bacterial damage deeper in the tooth that will necessitate an endodontic procedure and the higher the risk of loosing the tooth altogether due to cracking or other reasons. Hence, though the difference in out-of-pocket cost between receiving a more complex cavity procedure and a less complex procedure may be minimal to the patient (especially given dental insurance coverage) initially, the difference in severity may impact the consumer’s downstream costs and demand for further follow-up procedures. The potential harm to consumers in increasing the severity of procedures is discussed at length in Section 2.3.

Though consumers may have had repeated encounters with a dentist, quality is difficult for consumers to ascertain, especially because many dental conditions tend to be asymptomatic. When treatment alternatives presented to the patient are similar in out-of-pocket cost, time
cost, and cosmetic appearance, the dentist will have the ability to sway the consumer to procedures with higher probability of downstream procedures and/or with higher total reimbursement rates. Hence, the issues with physician agency in medicine are present also in dentistry.

Given the recent health insurance expansions, the degree to which providers have autonomy over the amount of low-value care being given to patients is strongly relevant to the policy discussions on how to design payment systems and innovate delivery systems to incentivize more efficient provision of care. Though there has been a lack of consensus in the demand inducement literature on whether demand inducement occurs and the degree to which it exists, the literature on how providers respond to supply-side shocks is small but growing. This literature has primarily examined survey data on providers and offices to look at how provider behavior and hiring decisions change in light of an insurance expansion, but little is known about whether and how providers change the content of visits in order to respond to an insurance expansion.

Conditional on the availability of the claims data, the dental care market is a promising setting to study the impact of a large shock in demand on treatment behavior. This is because any shocks in market-level demand is likely to impact dental practices more than medical practices for a few reasons. The first reason for this is that dental practices primarily operate under-capacity due to lack of market demand (Vujicic et al., 2013). Because the majority of dental practices operate under capacity and are able to use dental hygienists to provide routine preventive procedures for new patients with minimal cost to the office (other than the cost of dental hygienists’ labor) (Buchmueller et al., 2016), dentists are incentivized to receive rather than turn away new patients. In contrast, translating an increase in demand for medical care (such as in the case of a private insurance expansion) to access is a struggle in medicine (Bodenheimer and Pham, 2010; Bodenheimer et al., 2009; Colwill et al., 2008). Decker and Lipton (2015) also stresses that in the dental market, an increase in dental coverage will translate to larger increases in dental care utilization if payment
rates are higher, which is more likely to be the case in private dental coverage expansions relative to public dental coverage expansions. A less than one-to-one conversion from the number of patients demanding care to the number of patients desiring care – especially given private insurance coverage with higher payment rates relative to public insurance – is less likely in dental care.

The potential for inducement behavior suggests that dental providers may alter their treatment behavior in response to large shocks in market demand, allowing changes in inducement to be detected in aggregate (rather than claim-by-claim). Though the majority of dental practices are able to treat new patients with minimal increases in material cost, due to the use of dental hygienists for routine and preventive procedures, there is still a shadow cost of providing care to new patients. Given a fixed office capacity (i.e. the number of chairs in an office), the office may have less capacity to provide treatments, especially more time-intensive treatments that take up chairs for longer periods of time. Because of this, providing routine procedures and care to new patients may spillover into the care received by existing patients. Since dentists may be more likely to take on new patients relative to other disciplines, an exogenous increase in market demand in dentistry is more likely to lead to a dramatic change in treatment behavior, which is as a result more likely to be detected in the data.

To test the empirical predictions from the extension of the McGuire and Pauly (1991) model described in Chapter 2, I use dental claims from one of the largest dental insurers in the United States to examine how provider behavior may be affected by an insurance expansion that effectively facilitates access to providers. I use 2008-2014 dental claims from Delta Dental of Michigan, Indiana, and Ohio (DDMI) that traces providers across claims, patients, and years. This dataset is novel to the economics literature – dental claims historically have been difficult to acquire, and no other dental claims datasets used in the economics literature have been known to have the wide geographic variation that is

1This is also supported by the broader literature examining the effects of generosity of provider payment on Medicaid provider participation and access to care (e.g. (Polsky et al., 2015)).
present in the DDMI data. The DDMI data contains dental claims across all fifty states in the United States, with an average of 5.57 million unique individuals per year and an average of 9.22 million claims processed per year. Furthermore, DDMI holds 65% market share in its main states of operation (Michigan, Indiana, and Ohio), and captures more than 93% of providers in its dental network, which helps to ameliorate concerns about new enrollees switching between insurers or a change in insurance status leading to a change in provider choice. As a result, we can identify patients that are truly new to practices and to dental insurance plans. I also discuss at length what changes in demand inducement may look like empirically given the clinical and institutional details of the dental market to suggest what the welfare impacts on patients are.

The ultimate goal of this research is to analyze how substantial changes in office load (measured primarily in the number of patients per office) impact treatment behavior. As a result, this research is most concerned with whether providers’ treatment decisions respond to the size of a shock from the number of new patients added into each office. However, the simple correlation between changes in the number of patients in each office and the average treatment intensity and quantity across patients does not account for the fact that omitted variables, such as quality, may be influencing this relationship. A plausible story is that patients may perceive offices that implement more treatments or higher intensity treatments to be higher quality, and thus flock to these offices, leading offices that are higher intensity/quantity to have more patients. Hence, a plausibly exogenous shock that increases office load and is uncorrelated with the underlying quality of an office is needed to resolve this endogeneity problem.

To do this, I exploit a large dental insurance expansion stemming from the Affordable Care Act as a novel source of variation that leads to a significant increase in office load among offices affected by the expansion. As part of the Affordable Care Act, health plans were required to extend coverage to dependents between ages 18-26 by the end of 2010, with effects on enrollment appearing starting in 2011. Dental plans were not required to make
the same changes. However, many employer-sponsored dental plans did extend coverage to dependents up to age 26. This could affect dental coverage enrollment by 1) increasing take-up among dependents and 2) increasing take-up among families with dependents that may have had access to dental coverage for adults, but not for the dependents. Prior research has found evidence of the dependent coverage expansion even among survey data (Vujicic et al., 2014; Shane and Ayyagari, 2015), suggesting that the expansion is not DDMI-specific, but industry-wide. Curran (2016) also reports in the 2016 IBISWorld Dental Industry report that “[an] uptick in the number of children with dental benefits, coupled with more young adults (i.e. individuals aged 19 to 25) having private dental benefits, has provided a boon to the [dental care] industry”. The identifying variation that is used in this project comes from the fact that because the dependent coverage expansion among dental plans was strictly voluntary and stemmed from employer-level decisions, the degree to which markets were impacted by the dependent expansion varied and was not anticipated by dental providers in the market.

To ensure that the increases in county-level enrollment and in patient loads for dental offices are a result of an increase in market demand, rather than an increase in Delta Dental-specific enrollment, I instrument for the increase in demand using the simulated size of the expansion in each market, proxied by the ratio of the population directly eligible for the insurance expansion of interest. I find that a one standard deviation increase from the mean in the size of the eligible population generates a 2.59% increase in dental coverage enrollment for individuals under age 65, with spillovers in enrollment coming from the parents of those eligible for dependent coverage. This suggests that up to a 9.2% increase in the number of patients in each office is possible given a one standard deviation increase in the ratio of eligible individuals in the population. The office-specific analyses suggest a substantive demand shock for individual dental offices of a size in line with the county-level analysis, with offices one standard deviation above the mean experiencing an average 3.6% increase in the number of patients across all years in the post-implementation period, relative to the baseline year of 2008, with offices facing larger expansions experiencing up to an 9.5%
increase in the number of patients.

Using two-stage least squares, with the simulated size of the dependent expansion at the market-level as an instrument for increases in office load, I find that the sudden shock in office load from the dependent expansion leads to a statistically significant decrease in the average number of intensive cavity procedures across continuously insured patients and a statistically significant and sizable increase in the average number of diagnostic imaging procedures per continuously insured patient, and modest increases in the average number of cleanings per continuously insured patients. Because I include only patients who have been continuously insured throughout the time period, the increase in intensive cavity procedures is not from a sudden change in insurance coverage, thus removing any moral hazard effect or changes in underlying demand. The result taken together suggest that a sudden increase in an office’s workload leads to substitution away from intensive cavity procedures towards routine procedures. This is consistent with the predictions of models of demand inducement and provider behavior.

Given that the analysis in Chapter 4 is consistent with a theory of demand inducement, I discuss in Chapter 5 why demand inducement is an issue in the dental market and why an insurance expansion is only a partial solution to the problem of demand inducement among providers. Generally, catastrophic dental costs or catastrophic medical costs resulting from insufficient utilization of clinically effective preventive care do not fall upon the dental insurer. As a result, dental insurers are not incentivized to decrease the incentives for demand inducement nor to provide incentives for dental providers to increase utilization of clinically effective preventive care. I then discuss the policy levers available for addressing the misalignment of clinical efficacy and provider reimbursement, using the theory of optimal insurance and optimal coverage of preventive care. Chapter 6 then concludes.
CHAPTER 2 : Background

In this chapter, I outline first the economic theory for why providers may choose to prescribe services that patients would not otherwise demand given full information (demand induction) and generate testable predictions for what will occur in the event of an insurance expansion leading to an increase in the number of patients among practices. I then review the previous literature testing similar predictions and discuss the historical challenges, as well as areas for improvement.

Moving to the dental market more specifically, I review the clinical literature to describe how reimbursement rates are misaligned with effectiveness of dental treatment, which accentuates the incentive to prescribe procedures with potentially negative impacts on patients’ clinical outcomes because of the financial reward to the provider. Because many of these mispriced procedures are covered generously by insurers with little to no patient out-of-pocket costs, this implies that if patients had full information about the clinical effects and costs of treatment, they would not acquiesce to treatments with low clinical efficacy and high financial reward for providers. As a result, there is substantial incentive to prescribe low-value care to patients in the dental market. The data used in this dissertation then is introduced to further assess the validity of the assumptions in the theoretical model and more concretely discuss how reimbursement rates give rise to incentives to prescribe dental treatments for which patients with full information would otherwise reject in the dental market.

Given the substantive incentive to induce demand in the dental market and the disincentive dental insurers have to increase utilization of effective preventive care and decrease the plausible over-utilization of restorative care, the implications of the theoretical section suggest that increases in dental insurance coverage may be a partial solution to incentivize more preventive care and less restorative care. As a result, rather than exacerbating the problems of mispricing of procedures relative to their clinical efficacy and to patient net benefit, and
the resulting incentive to overuse mispriced procedures, increases in insurance coverage may be a short run solution to decreasing the incentive to overuse procedures without changing the payment structure of insurance plans.

2.1. Theory

2.1.1. Profit Maximizing Offices

I discuss here briefly how offices in a monopolistically competitive market would react to an increase in market demand, where they face potentially binding capacity constraints. This discussion uses the model discussed in McGuire (2000), which outlines a monopolistically competitive model with administered prices (where prices are always above cost for covered services), symmetric information, and quantity-setting offices.

In this model, providers can set take-it-or-leave-it offers to patients, where the offer of treatment optimally extracts all of the available consumer surplus for each patient, given a non-binding capacity constraint. A binding capacity constraint would effectively cause there to be an additional per-unit cost of production (the shadow cost). As long as the reimbursement for services remains above the cost of production with the per-unit shadow cost from a binding capacity constraint, then the profit per unit is strictly positive and the provider extracts all the consumer surplus from each patient as possible by setting quantity as high as the patient can tolerate without going to another provider. This is because the provider has the market power and non-retradability to extract all available consumer surplus even when prices are administered and providers set quantity.

In the monopolistically competitive model, a change in the number of patients that does not lead to a binding capacity constraint should not change how the provider optimizes at the patient level, but may instead change the composition of patients within the practice. This is because some of the new consumers that have come into the market may have a higher willingness to pay per unit of service, which allows the provider to extract more consumer surplus from these patients. Once a patient is within a practice, the provider chooses to
extract all the consumer surplus. However, providers may respond to a sudden influx of patients in the market by shifting towards patients with a greater willingness to pay per unit (so that they can extract more consumer surplus from these patients).

Suppose though that the monopolistically competitive office faces a binding capacity constraint. The office seeks to extract as much consumer surplus as possible from each patient, but is constrained by the capacity within the practice. Then, the office will extract as much as possible given capacity and cut down on services with low patient value first. However, there should be no change among the highest-value services because providers were already extracting all the available consumer surplus from provision of the high-value services.

Generally, the shift towards patients with higher willingness to pay in the event of a market expansion predicts an increase in quantity of services with no capacity constraint, but this is from a change in the patient composition in the practice. If the practice becomes capacity constrained from the market expansion, then there is a decline in low-value services, but no change in high-value services.

As a result, an examination of changes in treatment behavior among patients continually in a practice in the monopolistically competitive model should yield either no change (if capacity does not bind) or a decline in low-value services and no change or a decline in high-value services. There should be no increases in any type of service under the monopolistically competitive model.

2.1.2. When Offices Can Induce Demand

A useful theoretical framework for analyzing how providers respond to insurance expansions when there is the incentive and ability to induce demand is the McGuire and Pauly (1991) model which has been the basis of much of the empirical work aimed at detecting whether inducement takes place among providers and to what extent. The key element of this model is that providers receive utility from income and disutility from the effort put towards convincing patients to receive low-value care. This generally takes place in the form of
high intensity procedures for which the patient is ill-suited for and would not receive given perfect information. The main prediction of the model is as follows:

**Prediction 1.** All else fixed, an increase in the number of patients seen in a practice will lead to a decrease in inducement carried out per patient in the practice.

There are a few reasons for providers to 1) experience disutility from inducement effort and 2) decrease the amount of inducement when there is an increase in the number of patients within a practice. The first, discussed by McGuire and Pauly (1991), is that there is a “conscience” cost of inducement, in which providers feel guilty at their behavior and therefore receive disutility from increased efforts at inducement. The second, suggested by Dranove (1988), is that there are negative reputational effects from increasing inducement. Related to this is that as the number of patients increases, the probability of insurers or other stakeholders detecting inducement behavior increases, with punishments ranging from exclusion from provider networks in an insurance plan or litigation for fraud in extreme cases. A decline in inducement then could yield either 1) a decline in intensive services only or 2) substitution between high-intensity to low-intensity services.

A third reason for providers to decrease inducement when there is an increase in patient load is that providers may face a capacity constraint in the number of patients, the number of patient visits, and/or the number of treatments that can be provided. In the operations management literature, Paç and Veeraraghavan (2015) suggest that when the low-value care takes the form of treatments that are more highly reimbursed and require more time, congestion in the practice may act as a natural cost of overtreatment by imposing longer delays and higher waiting costs for consumers when demand exceeds supply. As a result, providers may substitute towards less intensive treatments that take up less time and space in the practice when there is a large influx of patients, and capacity cannot be adjusted in the short run. Incorporating a capacity constraint into the McGuire and Pauly (1991) model, with each service taking up varying levels of capacity in the practice (because some
services use up more materials, manpower, and office space than others), generates the following prediction.

**Prediction 2.** An increase in office size that causes the capacity constraint to be binding at initial levels of inducement leads to decreased inducement per service per patient, with stronger results for services that take up more capacity in the practice.

Moral hazard among the newly insured adds an additional layer of complication to models of provider behavior when an increase in the number of patients seen in practices is caused by an increase in insurance coverage among the population, which is directly relevant to this paper. Health insurance expansions may affect the quality and quantity of care received across all patients, due to increased demand through the avenues of both increased market size and increased moral hazard. We have discussed the intuition behind the impact of increased market size above. However, moral hazard among the newly insured may lead to increases in demand for procedures due to the change in the out-of-pocket price faced by consumers for medical care. This is well-documented in the literature, especially for the impact of utilization among the newly insured (for instance, Brook et al. (1984) and Finkelstein et al. (2012)). As a result, I separate patients into two different groups in the practice, the continuously insured and the newly insured. Though there are up to four potential groups of patients in the practice – 1) those who were previously and continue to be insured and seeing the dentist, 2) those who are newly insured and were not seeing the dentist previously, 3) those who are newly insured and were seeing the dentist out-of-pocket previously, and 4) those who are seeing the dentist out-of-pocket – the two that can be identified in the data are groups (1) and (2), the continuously insured and the newly insured. Because the effect of the insurance expansion used in this paper primarily increases insurance rates among those previously not seeing the dentist out-of-pocket (discussed later in Section V on data and measurement), I abstract away from groups (3) and (4), those who were seeing the dentist out-of-pocket without insurance at some point in time.
The newly insured who were not being seen in practices prior to gaining dental insurance face a shock in their out-of-pocket price for treatment. This is because previously, the out-of-pocket prices for this group was prohibitively high (so that they were previously not seeing the dentist without insurance) and declines after insurance receipt. As a result, the newly insured may both increase their consumption of dental services and be less resistant to inducement when the out-of-pocket price of services declines (especially for cleanings and X-rays) upon becoming insured in a dental plan. This leads to the following prediction for the newly insured:

**Prediction 3.** A decrease in price for the newly insured (who were not seeing the dentist prior to insurance receipt) leads to an increase in the quantity of services for the newly insured.

As a result, Prediction 3 is in direct contradiction to Predictions 1 and 2, which predict a decrease in quantity of services among both intensive and capacity-intensive services and a potential increase in quantity of low-intensity treatments (due to a decline in inducement for intensive services leading to substitution to low-intensity treatments). Hence, whether quantity increases or decreases for the newly insured is theoretically ambiguous.

To avoid ambiguous predictions, I focus attention on the continually insured in the practices who are not experiencing abrupt changes in plan design. This results in the following testable hypotheses:

**Hypothesis 1.** An increase in the number of newly insured patients in the practice will lead to a decrease in inducement for the continuously insured.

**Hypothesis 2.** When capacity constraints become binding, an increase in the number of newly insured patients in the practice will lead to stronger decreases in inducement for more capacity-intensive services among the continuously insured.

However, if the capacity constraint becomes binding and the effect of capacity especially
for more time- and capacity-intensive procedures (that generally tend to be more intensive services in dentistry) dominates the moral hazard effect for the newly insured, it may be possible to detect a stronger decline in the quantity of services provided per newly insured patient for more intensive services relative to less intensive services (such as cleanings and X-rays). This leads to Corollary 2.

**Corollary 1.** Hypothesis 2 may hold for the newly insured if the capacity effect dominates the moral hazard effect for the newly insured.

Overall, the model implies that there may be a change in the general equilibrium of the quantity and quality of services provided across all patients, and thus implies spillovers onto continuously insured patients. In particular, a decline in inducement implies both a decline in high intensity services that is substituted for with a possible increase in low intensity services for continuously insured patients. This is in contrast to the case of the profit maximizing office, which predicts 1) no change in treatment for continuously insured and continuously seen patients when there exists excess capacity and 2) only a decline or no change in the quantity of both high- and low-value services. Whether quantity and quality of services received by patients changes in response to an insurance expansion, the size of the spillovers to patients that were seen prior to insurance expansions, and the welfare consequences of such changes has yet to be explored. The full details of the extension of the McGuire and Pauly (1991) model for this paper are in the Appendix.

2.2. Prior Literature

The two strains in the literature examining variation in incentives to induce care leverages either changes in provider-to-population ratios (density) or changes in reimbursement (McGuire, 2000). Though changes in reimbursement, especially with regulated fees that are present in many healthcare markets, more directly influence the incentives to induce demand compared to changes in provider-to-population ratios, the subset of the literature focusing on changes in reimbursement has faced several problems.
First, a change in fees under the McGuire and Pauly (1991) model yields mostly ambiguous predictions about what occurs to supplier-induced demand because the substitution and income effects from a change in fees may cancel each other out. Hence, not only must changes in fees be large enough to cause providers to change their behavior, but income effects also must dominate any substitution effects (McGuire and Pauly, 1991), making detecting marginal changes in demand inducement difficult, which De Jaegher and Jegers (2000) point out is the only way to determine whether demand inducement exists in practice. For instance, Yip (1998) looked at Medicare fee cuts for previously overpriced procedures, which threatened to be a 26% loss of surgeon income assuming constant volume. The result was that volume increased for these procedures among both Medicare and private patients, which was then strongly suggested to stem from a strong income effect consistent with models of demand inducement. In contrast, Gruber et al. (1999) finds an increase in C-sections after an increase in reimbursement relative to vaginal deliveries. The differences may be due to examining small versus large changes in incentives for inducement - small changes may imply smaller income effects, whereas larger changes may imply more dramatic income effects. Second, there is difficulty in untangling patient-initiated changes in utilization from provider-initiated changes in utilization especially when a change in fees may reflect not only a change in provider payment but also patient payment, and when the data is unable to directly determine what is patient-initiated and what is provider-initiated. Dijk et al. (2013) attempts to make use of both a change in reimbursement systems (a shift from a combination of social and private health insurance towards compulsory single universal basic health insurance), which could arguably lead to a large income effect, in the Netherlands and data that distinguishes between patient- and provider-initiated utilization. Though they find positive evidence of supplier-induced demand, it is unclear whether their difference-in-differences specification passes the parallel trends test, which is a basic condition for the use of the difference-in-differences approach, due to their use of a limited time frame with one year prior to the policy change and one year after.

The McGuire and Pauly (1991) model is not the only model of demand inducement that
generates predictions for how changes in provider density will change treatment behavior. Another key model is Dranove (1988), which models patients as Bayesian learners with information about the frequency with which a provider overprescribes treatment. Hence, based on the reputation of the provider and the diagnostic skill of the patient, the patient will choose whether to consent to treatment or not. The result is that both the patient’s consent strategy and a utility-maximizing provider’s strategy both use cutoff rules. Hence, the provider may induce demand by lowering the cutoff and thereby recommending treatment for less severe clinical indications, but patients respond be increasing their cutoffs, thus limiting the amount of demand inducement that can be carried out by providers. Dranove (1988) notes that “as the physician/population ratio [decreases], each consumer’s information about particular physicians will [increase]”, thereby decreasing the incentive to induce demand. This is a prediction that is supported also by the McGuire and Pauly (1991) model, but stressing a different mechanism - negative reputational effects from increasing demand inducement. De Jaegher and Jegers (2000) and Reinhardt (1985) both point out that the positive relation between the physician/population ratio and inducement is the only prediction that distinguishes hypotheses derived from demand inducement models from those derived from the neoclassical model.

The literature thus far has been limited in the ability to empirically test the original McGuire and Pauly (1991) hypothesis of how a change in market size affects provider behavior in a fully rigorous way. An early series of papers attempted to take advantage of the clear empirical implications coming from changes in market size in McGuire and Pauly (1991) by examining how variation in the provider-to-population ratio affected treatment intensity. The smaller literature on demand inducement in dentistry has primarily used this strategy (Manning Jr and Phelps, 1979; Conrad et al., 1987; Mueller and Monheit, 1988). However, these papers suffered from endogeneity concerns, particularly because provider location choice is not exogenous from the taste for and demand for certain levels of treatment intensity in markets, which may then affect the provider density in markets. Dranove and Wehner (1994) famously clarified and emphasized this by testing an empirical strategy often
used among these papers by testing for inducement in childbirths, and found “evidence” of inducement in an area where there should have been none.

This paper most closely follows the vein of the Gruber and Owings (1996) and Currie and Gruber (2001) approaches, which use exogenous changes in market size for medical treatment. Gruber and Owings (1996) uses the declining fertility in the United States as an exogenous income shock to obstetrician/gynecologists during the 1970s. Because declining fertility rates are exogenous with respect to tastes for treatment intensity and changes in reimbursement levels, the authors could estimate the size of the income effect on treatment intensity, finding that within-state declines in fertility are correlated strongly with within-state increases in cesarean utilization. The Currie and Gruber (2001) paper uses a similar approach in looking at the effect of exogenous market expansions on treatment intensity, but use instead the differential timing and size of Medicaid expansions, finding that treatment intensity increased for childbirths among the previously uninsured, but decreased for those who were likely to have had held private insurance coverage prior to the expansions, and then to have switched to Medicaid. As in both Gruber and Owings (1996) and Currie and Gruber (2001), there cannot be much said about the levels at which inducement is provided at, but only the change in inducement due to the policy intervention. This implies that the size of the policy intervention must be large enough to induce a measurable change in inducement.

Policies impacting rates of insurance coverage, such as insurance expansions, that translate to increases in the patient load among practices may then be a promising area to look for policy interventions. However, part of the difficulty in the literature in assessing how providers alter their treatment behavior in response to changes in coverage rates comes from 1) inability to trace providers across patients and insurers in many claims datasets and 2) difficulty in finding an exogenous change in insurance coverage that is large enough to impact an office’s workload sufficiently. The degree to which office workload is affected by an insurance expansion depends on whether providers are incentivized and are able to
turn away patients. If providers are able to exert control over their office workload, then an insurance expansion will not lead to an increase in access for those previously uninsured, and supply-side decisions should not be substantially impacted by the expansion. Nonetheless, studying what the effects of insurance expansions on provider behavior is still an important open question, and examining different sections of the healthcare market that vary in their ability to translate insurance coverage to access to care may give a broader view of how insurance expansions may impact provider behavior given a certain provider landscape.

As a result, this paper also relates to the literature on the supply-side effects of insurance expansions, which is a developing area of study in the economics literature. So far, the status quo in the literature on the supply-side effects of insurance expansions has been to use self-reported provider data (Garthwaite, 2012; Buchmueller et al., 2016), which is unable to capture changes in dental treatment choices, though variables such as hours supplied per week by the dentist and dental hygienists that are not directly captured in dental claims data is available.

In the literature on the effect of insurance expansions, both Buchmueller et al. (2016) and Decker and Lipton (2015) specifically examine what occurs in public dental insurance expansions by looking at increases in the generosity of Medicaid adult dental benefits over time and across states, but are unable to examine changes in provider treatment behavior that may be important underlying mechanisms driving their results. While Buchmueller et al. (2016) focuses on the effect on supply-side behavior finds that dental providers respond to Medicaid expansions by increasing take-up of Medicaid patients and shifting work to dental hygienists, they are unable to examine how the content of visits change and thereby affect patient outcomes and welfare. Using a similar source of variation, Decker and Lipton (2015) finds that not only does increasing generosity of adult dental benefits increase utilization of dental services, but also seems to decrease the likelihood of severe dental problems. However, their data evaluating the clinical effect is limited to only leverages cross-sectional variation due to the limitations in the time period available for the data (one year only.
using the dental health outcomes available only in the 2008 National Health Interview Survey) and is unable to untangle where the improvements in dental health may come from. As in Buchmueller et al. (2016), Decker and Lipton (2015) is also unable to examine what occurs with utilization among patients who already had insurance and what the net effect on supply-side choices and treatment behavior may have been. Furthermore, it is unknown how the impact of public expansions in dental insurance may differ from private expansions - Decker and Lipton (2015) also suggests that the effects of increases in coverage may have a larger effect on the use of dental care if reimbursements to dentists are higher.

In general, there is little information both on how insurance expansions affect treatment behavior among providers and in the broader literature using the exogenous variation provided through insurance expansions. This literature has previously discussed the effects on selection and crowd-out (Hackmann et al., 2015; Gruber and Simon, 2008), as well as on access, utilization, and health outcomes (Finkelstein et al., 2012; Mueller and Monheit, 1988; Kolstad and Kowalski, 2012). However, none to date have examined the impact of insurance expansions on provider treatment choices. This is primarily been because the service-specific data rarely exists especially for dental markets (Sintonen and Linnosmaa, 2000), and prior insurance expansions have been relatively small in size and have not differentially affected markets in unpredictable ways, as has been the case with the recent implementation of the ACA.

2.3. What Does Demand Inducement Look Like in Dentistry?

Prior literature on supplier-induced demand in dentistry has emphasized that historically, the supply of dental services has exceeded demand, especially due to the reduction in dental disease that took place in the 70s and 80s (Grytten et al., 1990) that was hypothesized to come from increases in fluoridation and use of fluoride toothpaste. In this context, researchers were concerned about the possibility of dentists inducing demand to make up for the fall in income from the decline in demand for dental services. Few researchers have defined clearly, however, where the incentives to induce demand arise in dentistry.
Dranove (1988) writes that "inducement models...suggest that physicians induce demand by recommending procedures even though the available clinical information indicates that the expected costs of the procedure (to the patient) exceed the expected benefits." Hence, in this section, I seek to show that there is incentive to induce demand in dentistry. To do this, I address 1) what the clinical recommendations and summarize briefly the clinical evidence that exists (or does not exist) for each recommendation, 2) the clinical and financial ramifications for the patient in increasing intensity of treatment and 3) whether the payment structure for dental procedures reimburse more strongly for higher intensity of care and to what extent.

Dental services are broadly separated into seven basic types, which are as follows: 1) preventive care, such as cleanings and routine office visits encapsulating exams and X-rays; 2) restorative care, such as fillings and crowns; 3) endodontic care, such as root canals; 4) oral surgery; 5) orthodontics, such as retainers and braces; 5) periodontics; and 7) prosthodontics, such as dentures and bridges.

There exists a robust literature with randomized clinical trials supporting the efficacy of several low-cost, low intensity preventive procedures especially for certain populations, such as fluoride varnish (Marinho et al., 2002) and the use of sealants among children and silver diamine fluoride (Liu et al., 2012; Rosenblatt et al., 2009; Zhi et al., 2012). Furthermore, there has also been some evidence that improving dental hygiene habits can not only prevent (especially through the use of fluoride toothpaste as in Marinho et al. (2002)), but also reverse early cavities. This is due to how cavities progress. The National Institute of Dental and Craniofacial Research (2013) writes that "[tooth] decay is the result of an infection with certain types of bacteria that use sugars in food to make acids...[which over] time make a cavity in the tooth". Hence, when a tooth frequently becomes exposed to acid, this can cause the protective enamel surrounding a tooth to lose minerals. Over time, enamel may become "weakened and destroyed, forming a cavity" (National Institute of Dental and Craniofacial Research, 2013), though before a cavity is formed, enamel can repair itself using minerals
from saliva and from fluoride (via toothpaste or other sources). Hence, application of fluoride or improved brushing habits can reverse a potential cavity. "Current dental caries management considers caries disease to be a dynamic and reversible process" (Braga et al., 2010), because "dental caries is a dynamic process fluctuating between demineralization and remineralization over time" (Rochlen and Wolff, 2011).

However, these interventions tend to either not be reimbursed highly enough to incentivize dentists to use them or not reimbursed at all by dental plans (Niederman et al., 2017), both public and private. Because these procedures are estimated to be effective to decrease future caries by 40% (fluoride varnish) and up to 80% (silver diamine fluoride, sealants), they potentially pose a threat to the future income stream of dentists by diminishing the future number of cavities that will enter the practice, especially because providers are reimbursed on a fee-for-service basis. Thus, these procedures are under-utilized, though the clinical literature supporting these interventions date back more than fifty years (Niederman et al., 2017) and one of the stated Healthy People 2020 goals are to improve sealant usage among children and adolescents up to age 15. The effect of silver diamine fluoride to arrest caries has been known for more than a century (also called "Howe’s solution" after Howe, who reported on its effects on caries prevention in 1917), though fell out of use fifty years ago. I discuss why dental insurers have not better reimbursed these procedures in Chapter 5.

In contrast, the majority of services that are covered by dental benefits have not been shown to clinically reduce the prevalence of dental cavities. Currently, dental benefits generally cover annual or twice-yearly office visits for an exam, cleaning, X-rays (generally one set of bitewing X-rays a year, with four films to a set), and sealants (eligibility for coverage for sealants is typically age-determined) (National Association of Dental Plans, 2014), with additional visits requiring patients to pay out-of-pocket for additional routine procedures. For other non-routine or non-preventive procedures, the consumer typically is required to pay some amount of the procedure costs. Notably however, there are no clinical trials demonstrating that twice-yearly oral evaluations and cleanings (prophylaxis)
reduce prevalence of dental caries (Niederman et al., 2017; Bader, 2005; Davenport et al., 2003). Similarly, there has been little or no data demonstrating that dental surgeries that extract tooth decay followed by fillings reduces or prevents the underlying bacterial infection from continuing to destroy further tooth structure in the mouth (Niederman et al., 2015). Furthermore, there are systematic reviews that find that traditional fillings that remove tooth structure in the process of treatment lead to significant increases in the probability of adverse events relative to sealing early cavities or using atraumatic restorations (Ricketts et al., 2013; Schwendicke et al., 2013; Niederman et al., 2015). The dental literature has only recently been highlighting the lack of robust evidence supporting the efficacy of the majority of traditional dental treatment (Ricketts et al., 2013), and this has come to light in the popular media as well recently in a series of news articles (Frakt, 2016; Carroll, 2016; Holmes, 2016; Donn, 2016; Saint Louis).

As for X-rays, there is not a robust evidence base demonstrating that traditional imaging techniques are effective in diagnosing cavities. Meurer et al. (2015) reviewed the literature comparing dental imaging to visual inspection in diagnosis of common dental conditions among children and adolescents and found that the evidence is mixed, but that dental imaging and visual inspection are comparable. Some of the mixed evidence may be due to the variation among dentists in defining whether a tooth is carious or not (Greenfield Boyce, 2005). However, because X-rays are two-dimensional and tooth damage three-dimensional, "the core technology of X-radiation allows detection of proximal caries lesions only when they are at least halfway through the enamel radiographically" (Berg, 2014). Furthermore, there is significant differences in radiographic interpretation across dental providers (Balto and Al-Madi, 2004). Hence, the American Dental Association suggests that though the frequency of X-rays is up to the dental provider depending on the individual patient’s risk for cavities, adults with regularly scheduled professional care and at generally low risk for dental caries are recommended to have one set of posterior bitewings once every two to three years. ¹

¹It should also be noted that there exist other detection methods available to dentists for diagnosing
Despite the lack of evidence on the effectiveness of oral evaluations and cleanings and X-ray imaging, annual or twice-yearly office visits for examinations, cleanings, and X-rays are typically covered in full by dental insurance plans. The 2013 American Dental Association Survey of Dental Fees suggests that a routine visit with an oral evaluation (CDT code D0120 for established patients), four films of bitewing X-rays (D0274), topical application of fluoride (D1204), and an adult prophylaxis (cleaning) (D1110) could allow the provider to reap an average of $216.23 in total reimbursement and as much as $286, based off of the average and 95th percentile reported fees from general dental practitioners in the East North Central Division of the United States.

Because the profit margin for routine procedures is arguably higher than the profit margin for most other dental services, dentists would tend to prefer providing routine procedures over restorative procedures. Multiple dentists have asserted this to the author in informal discussions, but to estimate roughly the costs of routine procedures relative to restorative procedures, I use mean Medicaid procedure fees across the ten most populous states (California, Florida, Georgia, Illinois, Michigan, New York, North Carolina, Ohio, Pennsylvania, and Texas). The average Medicaid reimbursement for a visit that includes a periodic oral evaluation, prophylaxis (cleaning) for an adult, topical fluoride varnish, and a set of bitewing X-rays (four images) is approximately $96. The roughly estimated profit of a routine visit comprised of these procedures is then more than $150. Furthermore, many routine services are in the scope of practice for dental hygienists in most states, which likely drives cavities that are typically not covered by insurance, but which may allow dentists to persuade patients into cavity treatment for teeth with pre-carious lesions. Recent technological developments for early caries detection tools, such as light-based imaging (Wilder-Smith et al., 2010), has allowed for early detection of changes in the tooth instead of relying on X-rays or visual inspection by the dentist, but have been alleged to contribute to false positives or used to prescribe restorations. Though this technology could be used to identify weak spots in the tooth that would benefit from, for instance, fluoride application, there have been reports of using this technology to diagnose pre-cavities as cavities (Greenfield Boyce, 2005), though there has not been research to substantiate these claims. Furthermore, not all methods can accurately detect early cavities and may result in both false positives and false negatives (Zandoná and Zero, 2006). Hence, early caries detection methods should not be used to justify premature restorative intervention (Zandoná and Zero, 2006). Currently, insurance coverage for early detection methods is very limited, so dentists may offer scans from early detection methods for free as part of a regular office visit or cleaning (Johannes, 2015).

This is in lieu of better estimates of the cost for care, which the author thinks is likely to be driven heavily by the amount of time that a dentist and his or her staff spend on the examination and the cleaning. To my knowledge, there has not been any good consensus on how long routine visits take.
down the underlying cost incurred by the dentist for these services, since the dentist’s time can be better spent providing other services that might generate a higher profit margin in a shorter period of time. In contrast, one-surface amalgam fillings in the East North Central Division of the United States (Illinois, Indiana, Michigan, Ohio, and Wisconsin) are reimbursed an average of $118.93 but with an average Medicaid reimbursements across the ten most populous states for one-surface resin-based composites of $52 to $53, routine visits are estimated to be more than twice as profitable than cavity fillings. I note that using Medicaid reimbursements to estimate costs for non-routine dental procedures is likely an underestimate of the cost for carrying out these procedures, since the state Medicaid programs try to disincentivize the provision of non-routine procedures. Hence, the profit margin for a routine visit is arguably higher than that from one-surface fillings.

Given no restrictions on the number of routine visits per patient, it is likely that a profit-maximizing dentist would seek to increase the number of routine visits per patient as much as possible and solely run their practice on routine visits. However, because insurers place yearly limits on the number of routine procedures per patient with full coverage (with additional routine procedures usually being charged to the patient) and there is a significant time cost for patients in traveling for additional routine care, this places a limit on how many routine visits a dentist may persuade a patient into. Hence, it is unlikely that excess routine care (where the cost to the patient outweighs the clinical benefit) is being prescribed beyond the yearly constraints placed on utilization of routine procedures imposed by insurers.  

Once a dental provider has maximized the number of routine procedures that can be administered per patient, it is possible that demand inducement takes place among cavity

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3There is also an argument here, given the lack of clinical evidence supporting the efficacy of routine procedures in reducing or preventing caries, that the simple use of routine procedures is demand inducement in and of itself. However, what also matters here is the belief of the dentist administering care and whether they believe that they are inducing demand or not. If a dentist provides a service with no clinical value that insurers encourage them to administer and that they believe improves patient outcomes and welfare, then to the dentist, encouraging patients to receive the clinically ineffective service is not demand inducement. Furthermore, I would like to note here that the lack of clinical robust evidence does not necessarily mean that these services are necessarily of no clinical value, but merely indicates that there is yet no evidence to support their clinical value. In contrast, however, there are treatments for which there is robust evidence of efficacy that will be discussed.
procedures. This is because there is substantial financial incentive to increase severity of cavity treatment. For instance, national average fees for general practitioners in Illinois, Indiana, Michigan, Ohio, and Wisconsin suggest that a dentist could reap an average of $131.69 additional from going from a one-surface to a three-surface resin-based composite filling (for a posterior tooth), with the one-surface fillings costing an average of $155.83 and the four-surface fillings $287.52 (American Dental Association, 2014). Furthermore, because X-rays are two-dimensional and typically do not show the extent of tooth damage, X-rays are not usually required by insurers to justify cavity filling procedures. Hence, there is generally no evidence that an insurer or a patient is able to latch onto which would justify the size of a cavity filling.

Increases in the size of a cavity filling can have detrimental effects on patient cost and outcomes. Ricketts et al. (2013) writes that "removal of all [tooth] decay has some disadvantages, including damage to the nerve of the tooth, toothache and possibly weakening of the tooth structure". The larger the filling, the more structure that is removed from the tooth and the higher the likelihood of a crack in the tooth - which requires follow-up care such as a new filling, crown, root canal, or an extraction (American Association of Endodontists, 2016)\textsuperscript{4} - or for a general failure of the restoration\textsuperscript{5} (Bernardo et al., 2007). The risk of a dental restoration failing is non-trivial - "it has been estimated that the replacement of failed restorations constitutes about 60 percent of all operative work" (Bernardo et al., 2007). Furthermore, fillings typically need to be replaced every five to fifteen years depending on the type of material used and the stress that the filling is subject to, but each time a filling is replaced, more of the tooth structure necessarily needs to be removed. As a result, an increase in the size of a filling increases the patient's future likelihood of needing further intensive treatment on the same tooth and increases the future expected cost of maintaining the condition of the tooth. Specific cost estimates of the downstream costs of maintaining

\textsuperscript{4}From a clinical point of view, extractions are the worst case scenario.

\textsuperscript{5}Failure occurs when a restoration reaches a level of degradation that precludes a level of degradation that precludes proper performance either for esthetic or functional reasons or because of inability to prevent new disease" (Bernardo et al., 2007)
cavity fillings of different sizes were unavailable, but a study conducted by Delta Dental found that

...over a person’s lifetime it costs $1,788 to maintain a single filling on an anterior tooth and $2,108 to maintain one in a premolar. On average, patients who develop cavities in their molars between ages 7 and 12 require more than $1,000 in services by age 40 to maintain each restoration.

These estimates do not include the risk of a restoration failing and consequent intensive follow-up treatment. Bernardo et al. (2007) ran a randomized controlled trial comparing survival of amalgam and resin-based composite posterior restorations and found that 10.1 percent of primary restorations failed within seven years, regardless of the type of material used in the restoration. To give an idea of the cost involved in follow-up care for a failed restoration that necessitates follow-up endodontic work, the average fee for endodontic therapy on a molar in the East North Central Division of the United States is $945.51 (American Dental Association, 2014)\textsuperscript{6}. With limited insurance coverage for intensive dental procedures, this represents a potentially large financial loss to the patient. Hence, though a patient may not face substantial increases in immediate out-of-pocket cost due to an increase in the size of a filling, the potential cost and risk to a patient from an increase from a larger filling is likely to be non-negligible. Because of the decrease in consumer welfare (both risk and expected future costs increase from an increase in the size of a cavity filling), holding fixed the true underlying severity of the patient’s oral condition, an increase in the severity of a cavity procedure instigated by the dentist would meet the definition of demand inducement as defined by Dranove (1988).

Increasing the size of a cavity filling is perhaps the least detectable type of demand inducement from an insurer and patient’s point of view, but there also exists another possible type of inducement that a general dentist might be able to take up (but at higher risk of patient

\textsuperscript{6}This is using the average fee for procedure code D3330, which is for endodontic therapy on the inside of a tooth to treat infected pulp and does not include the cost of the final restoration (i.e. a crown)
pushback or insurer detection) - treating complex cases that would typically be served better by referral to a dental specialist. In dentistry, general dentists are licensed and trained to practice all areas of dentistry and only 20% of dentists have specialty training, which requires further training in a residency or advanced graduate training program after dental school. Dental specialists have further training in specific areas (such as root canals for endodontists or cosmetic and restorative procedures for prosthodontists) that may allow them to have a wider range of experience dealing with routine and complex cases. Though general dentists are allowed to implement treatments that dental specialists train specifically in, clinical decision-making differs significantly between general practitioners and dental specialists (Balto and Al-Madi, 2004; Bigras et al., 2008), and treatment by specialists has been found to yield better quality outcomes (Abei et al., 2004; Marques et al., 2011; Alley et al., 2004; Dugas et al., 2002) and less time on treatment (Marques et al., 2011).

The dental literature, along with anecdotes from individual dental clinicians or faculty, has suggested that "[decisions] made to treat or refer may be a means for [general dentists] to adapt to changing economic demand" (Gilbert et al., 2015). Though clinical findings tend to support that specialty treatment administered by dental specialists yield better outcomes for the patient, general practitioners may choose to administer specialty treatments themselves or keep complex cases within their practice instead of referring to a dental specialist especially when patient inflows are low. Furthermore, because insurers typically do not provide extensive (or any) coverage for more intensive procedures and dental plans are protected from financial risk through the use of annual dollar maximums, there is little incentive for insurers to require general dentists to refer patients out to specialists for more intensive procedures. Additionally, specialists may charge higher prices for the same procedure, which is an added incentive for insurers to limit specialty referrals, such as in

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7An exception to this is (Esfandiari et al., 2006), which was a randomized controlled clinical trial examining patient satisfaction and the number of unscheduled visits up to six months following procedures for dental prostheses carried out by experienced specialists relative to new general dentists, and found no statistical difference in outcomes between specialists and new general dentists.

8Carman (2010) has a thorough literature review of the differences in outcomes of endodontic treatment between endodontists and general practitioners, and factors driving the decision to refer patients to an endodontist.
the case of some dental managed care plans (Cottrell et al., 2007). Patients also generally do not refer themselves to most dental specialists (Cottrell et al., 2007) and referrals take place primarily under the direction of the patient’s general dental practitioner. Hence, self-referrals for specialty treatment, such as root canals and implants, may be a type of demand inducement that general dental practitioners can engage in.

There is also potential for the majority of dentistry as currently implemented in dental practices to be defined as demand inducement, given the lack of clinical evidence for common dental procedures and the wide support for the efficacy of sealants, fluoride varnishes, silver diamine fluoride, and other low-cost preventive procedures. However, I emphasize here that the lack of clinical evidence for these procedures tends to be because of faulty study design, and may not mean that common dental procedures have no efficacy in preventing future cavities or in improving the oral health of patients. Furthermore, whether prescription of a higher intensity treatment (such as a prophylaxis treatment / cleaning over a sealant) is demand inducement depends also upon the viewpoint of the clinician. If the clinician believes that he or she is doing the best for the patient, and is perhaps unaware of other recourse for treatment, then we cannot define that the prescription of a higher intensity treatment is demand inducement. But what is perhaps more concerning is if dentists are fully aware of the efficacy of these preventive procedures but do not prescribe them because reimbursement rates for these procedures are mispriced by dental insurers. Birch (2015) emphasizes that even with effective dissemination of the evidence on preventive dental procedures, providers operating under fee for service arrangements "rely on a constant flow of patients with oral disease in need of treatment.. [and that reducing] oral disease in the population reduces the size of the future market for treatment" (Birch, 2015). In this case, the incentive to induce demand is exacerbated by the mispricing of procedures carried out by dental insurers. I discuss this further in Chapter 5.

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9 Though the differences in clinical quality and outcomes of treatment may differ substantially between general dental practitioners and dental specialists, general dental practitioners may offer a lower price to patients (especially if patients are in dental plans with limited networks) or increased convenience over dental specialists. Hence, some of the loss in patient welfare from having a complex procedure done by a general practitioner may be recouped by the gain from experiencing lower costs or increased convenience.
The next question to ask after defining the plausible forms of demand inducement in dentistry is the following: is demand inducement welfare improving for patients? Labelle et al. (1994) stresses that whether or not physicians induce demand is not as important as the effects on patient welfare and De Jaegher and Jegers (2000) emphasize through their model of provider behavior that increases in demand inducement could be welfare-improving for both patients and providers. Similarly, Carlsen et al. (1998) suggest that decreases in treatment intensity or quantity could result from rationing, which implies a negative welfare effect upon patients who would likely benefit from utilization. However, given the clinical background outlined in the previous subsection, these concerns are less likely to hold in this setting. As discussed earlier, increases in the size of a filling put a patient at greater risk for adverse events, holding fixed the severity of the patient, as do self-referrals from general practitioners for more complex intensive procedures.

As a result, in this section we conclude that there is extensive room for dentists to induce demand, because the structure of dental payments for treatments is highly misaligned with the existing clinical evidence for the efficacy of dental treatments, and because there is little ability for insurers or patients to detect whether or not increases in treatment severity are warranted by the underlying oral condition. In particular for general dental practitioners, there is incentive to increase the size of dental fillings and self-refer patients for more complex dental procedures (rather than referring out to a specialist).

2.4. Conclusion

There is a general concern that while there may be societal welfare gains from increased provision of clinically effective preventive dental procedures, the current structure of dental insurance and reimbursements to dental providers and the practice patterns of dentists tends to incentivize restorative over preventive care.

However, the demand inducement model suggests that even when there is an incentive to induce demand for more intensive, restorative procedures, an increase in private dental ins-
surance coverage may decrease the incentive to induce demand and lead to shifts away from restorative procedures towards preventive procedures. Hence, rather than exacerbating the problem of provider-initiated overutilization of restorative care and under-utilization of preventive care, a private dental insurance expansion could provide at least a short run solution to improve provision of preventive dental care. Given the monetary and political costs of reforming the entire dental system (dental insurance, provider payment, and provider practice patterns), increasing dental insurance coverage may be a more efficient way to alleviate some concerns about demand inducement in dentistry.

2.5. Tables and Figures
Table 1: Medicaid Reimbursements for the Ten Most Populous States

<table>
<thead>
<tr>
<th>CDT Code</th>
<th>Procedure Description</th>
<th>CA</th>
<th>FL</th>
<th>GA</th>
<th>IL</th>
<th>MI</th>
<th>NY</th>
<th>NC</th>
<th>OH</th>
<th>PA</th>
<th>TX</th>
<th>Mean</th>
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<tr>
<td>D0120</td>
<td>Periodic oral evaluation</td>
<td>$15.00</td>
<td>$22.29</td>
<td>$22.77</td>
<td>$28.00</td>
<td>$14.89</td>
<td>$25.00</td>
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<td>$20.00</td>
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<td>D1110</td>
<td>Prophylaxis - adult</td>
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<td>$36.00</td>
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<td>$30.00</td>
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<td>Bitewings (4)</td>
<td>$18.00</td>
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Note: 2016 fee schedules were obtained for Florida, Illinois, Michigan, New York, North Carolina, and Texas. California’s fee schedule is from 2014, Georgia’s from 2013, and Pennsylvania’s from 2015. Ohio’s fee schedule was from 2016 for D1206 (fluoride varnish) and 2008 for D0120 (periodic oral evaluation - established patient), D1120 (prophylaxis - child), and D2330 (topical fluoride varnish). We coded the reimbursement rate for D1206 in California to be $18, but the reimbursement varies by age of the patient in California - $18 for patients between ages 0-5 and $8 for those between ages 6 to 20. D2330 (protective restorations (ITR)/sedative fillings) are not listed or covered in New York, Ohio, and Pennsylvania, so the range of reimbursement reflects that the reimbursement rate is effectively zero in this state for this procedure. No states reimburse for the use of silver diamine fluoride (D1354). For the fee schedule URLs for each state, please refer to the Figure 1.
## Figure 1: Medicaid Rates References

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CHAPTER 3 : The Dental Market

In this chapter, I begin by discussing why the dental market is an intriguing setting to study the impact of insurance expansions on provider behavior while introducing the institutional detail of this market. The lack of data on the dental market has been the main restriction in fully characterizing and studying this segment of the healthcare market, so I introduce then how I resolve several issues by introducing the data source for this dissertation in Section 3.3. To give a sense of generalizability, I compare the data to known information about the dental market discussed in the previous chapter in Section 3.4.

I then move to discussing the policy intervention in this market that serves as the main source of variation leveraged in this dissertation (the dependent coverage expansion) in Section 3.5 and compare the estimates from prior work on the size of the impact of this specific expansion to estimates generated by the data in Section 3.6. I conclude then by discussing the potential demand-side effects of such an expansion for the newly insured patients.

3.1. Dental Market Summary

The dental care market is a promising setting to study the impact of private insurance expansions on provider behavior, because 1) the uninsurance rate in dental care is especially pronounced relative to medical care, 2) dental offices are more likely to take up the newly insured population as new patients, and 3) dental providers have room to induce demand without detection by both patients and insurers. I discuss and develop these three points below.

First, dental insurance accounts for 9.7% of the health insurance industry (Curran, 2016), and is striking for the rate of uninsurance compared to the medical and health insurance industry – an estimated 33.9% of consumers in the dental market receive dental care without insurance, compared to an estimated 8.7% in medical (Curran, 2016). There are several
possible reasons for this, which are the following:

1. There is no federal program that serves as a reliable vehicle for dental benefits (such as Medicare and Medicaid\(^1\)). Instead, the majority of dental insurance enrollment comes from employer-sponsored dental plans.

2. Services that are most generously covered in dental insurance are routine and preventive procedures, instead of services that take place upon emergence of unpredictable and severe health ailments. These preventive and routine procedures are services that individuals may feel can be delayed until symptoms of an oral condition appear. Hence, demand for routine dental services may not be very high and as a result, demand for dental insurance may not be very high, especially if there is no employer-provided subsidy for dental premiums. Instead, demand for dental services is typically driven by increases in disposable income.

As a result, take-up of dental insurance is primarily located among employed individuals, and prior to 2011 did not necessarily cover their dependents, leaving a large segment of the population without dental insurance. An industry-wide expansion in dental insurance coverage among employers may then lead to a high take-up rate.

Second, increases in dental insurance rates are likely to translate into access to dental care, because dental practices tend to operate under-capacity. Declining demand for dental care services has been explained previously by improvements in public health interventions for oral care (such as fluoridation and diffusion of good dental hygiene habits among the population) leading to decreased rates of oral conditions in the population. Using data from the American Dental Association Health Policy Institute’s Survey of Dental Practice, Vujicic et al. (2013) found that 42% of solo practitioners reported being “not busy enough” in 2012, and that wait times for a general practitioner dental appointment have declined

\(^1\)Some state Medicaid programs do offer dental benefits, but these tend to be easily cut when there is a state budget deficit. Hence, there are fluctuations in the generosity and availability of Medicaid dental benefits (a fact that was leveraged in Buchmueller, Miller, and Vujicic (2014)), though there are no changes in Medicaid dental benefits in the main states of analysis in this paper during the timeframe of interest.
steadily over time from an average of 11.3 days to 5.4 days. These suggest that there is substantial room for absorbing new demand for dental care among dental practices.

Similarly, Buchmueller et al. (2016) suggest that dental offices are even willing to accept new Medicaid patients, which has been a group for which reimbursement rates to the provider are historically low. They examine the effect of expansion of Medicaid dental coverage, and find that dentists are able to increase their take-up of newly insured Medicaid patients. This did not impact the number of visits or the number of privately insured patients in the practice, indicating that the dentists had sufficient capacity to accommodate the increased numbers of patients. This implies that dentists are able to and to some extent are willing to take on new patients when there is a market expansion, which separates the dental industry to some extent from the medical industry where an increase in coverage does not directly lead to an increase in access (McCormick et al., 2012). This ability to take on even new patients with the lowest reimbursement rates for providers suggests that there is excess capacity in practices to take on new patients suggests that dental providers has the scope and financial incentive to induce demand.

The ability of dental practices to take on new patients may not only be because of operating under-capacity, but also may be directly related to their ability to use dental hygienists, especially for providing routine preventive procedures for new patients with minimal cost to the office. Dental hygienists are paid a median of $34.77 per hour (BLS, May 2015) and tend to work part-time. In comparison, topical fluoride applications are paid more than $30 per person, and prophylaxis (cleaning) costs between $60-$80 per person (ADA), and each of these procedures generally take less than an hour and can be carried out by dental hygienists. Buchmueller et al. (2016) suggest that offices located in states with less restrictive scope of practice laws for dental hygienists, which regulate the types of treatments that dental hygienists can undertake without the presence of the dentist in the office, are more able to take on new (Medicaid) patients without substantially increasing wait times in the practice. As a result, the use of dental hygienists further augments the ability of
dental practices to accommodate new patients.

However, as suggested by Section 2.1 discussing the model of provider behavior, there is still a shadow cost to providing care to new patients, which is that given a fixed office capacity, the office may have less capacity to provide treatments. Though dentists may be able to expand the hours worked by a dental hygienist in the practice to accommodate more patients, the practice may still become constrained in capacity in the short run, either because of insufficient physical space in the practice (i.e. not enough chairs) or because of an inability to expand dental hygienist labor supply sufficiently to meet demand (i.e. when it becomes necessary to hire an additional dental hygienist in the practice).

Finally, dental providers have room to induce demand without detection by both insurers and patients. An example of this arises from one of the most common procedures - cavity fillings. Though a common and relatively simple procedure, reimbursements vary with the size of the filling, going from $88 to $350 per filling (King, 2011), and X-rays typically do not capture the full extent of the tooth damage. Rather, the extent of the damage is known only when the dentist drills into the tooth, and due to the differences in reimbursement for simple versus more complex cavities, the dentist has an incentive to carry out the procedure for a larger filling than necessary. This can be done without penalty from the insurer or patient because there is no way to detect at a claim-by-claim level whether the dentist induced demand for a higher intensity procedure than would have otherwise been demanded by the consumer with perfect information. Inducement at an individual claim level is therefore neither observable nor verifiable.

The treatment of dental caries (also known as cavities) is an area with a non-trivial amount of potential waste - preventive treatment, such as fluoride and sealant application, exists and is low cost to administer and highly effective, yet 18% of the dental industry’s revenues comes directly from caries treatment and 20% from radiographs (which may be involved in caries treatment). Other treatment areas are similar - though consumers may have had

\[\text{In comparison, fluoride and sealant applications, which have been shown to substantially decrease the}\]
repeated encounters with a dentist for cleanings and similar preventive procedures, quality is difficult for consumers to ascertain, especially because many dental conditions tend to be asymptomatic. When treatment alternatives presented to the patient are similar in out-of-pocket cost, time cost, and cosmetic appearance, the dentist will have the ability to sway the consumer to procedures with higher probability of downstream procedures and/or with higher total reimbursement rates.

These characteristics of dental practices (operating under capacity, use of dental hygienists to provide low-cost care, and fixed capacity constraints in the short run) suggest that an insurance expansion resulting in an increase in market demand for dental services may lead to a more dramatic change in treatment behavior, which is as a result more likely to be detected in the data. The Buchmueller et al. (2016) paper is suggestive of this. First, though there was a statistically significant increase in wait times, the effect was quantitatively small. Furthermore, they found that a ten percentage point increase in dental coverage only led to an increase in dentists’ own labor supply by 0.6 hours per week. In contrast, there was an additional three visits per week from an increase in coverage of ten percentage points. This suggests that the content or the length of visits diminished, and indeed they find that average visit length falls by one tenth of a minute to one minute. Though the effect seems small and is statistically insignificant, one should keep in mind that Buchmueller et al. (2016) worked with 1) survey data on practice behavior, and did not directly observe changes in visit length; and 2) worked with expansions that may have been relatively small in scope. As a result, they were likely underpowered to find a statistically significant effect on visit length.

Though the dental care industry seems to be a promising area of study to detect changes in treatment behavior in response to shocks affecting office size, the literature was previously limited by the difficulty of obtaining detailed data on dental utilization, especially at the risk of caries especially among young adults, account for only 8% of dental industry revenue in 2011. Only very recently has there been a move among dental insurers to use and reimburse CPT procedure codes for dental prevention.
practice-, provider-, and patient-levels for a variety of insurance statuses (over multiple private insurers, public insurance, and the uninsured). Some efforts via survey data, such as the American Dental Association’s Survey of Dental Practices, have been carried out to examine nationwide practice decisions, but so far the data required to carry out a dental version of the Dartmouth Atlas (which documents variation in medical expenditure and use for the Medicare population) does not yet exist.

On the private dental insurance front, there have been some piecemeal efforts at consolidating dental claims across private insurers, however, such as FAIR Health data or some state APCD databases (such as Massachusetts). However, these tend to be costly, even at the institutional levels, and limited in research applications, due to data use agreements that restrict the use of provider- and plan-level masked identifiers. In terms of public insurance, Medicaid dental data can be obtained through arrangements with each state government, but the degree of difficulty varies, due to significant administrative burden.

Finally, the lack of data on the uninsured is especially significant in dental care, even compared to the magnitude of the problem in medical care, because of the prevalence of patients receiving dental care without any form of insurance (estimated to be between 30-40%). For medical care, the utilization patterns among uninsured patients can be observed in data either because 1) without insurance, medical care is unaffordable and thus is not utilized, and 2) when the lack of medical care becomes untenable for the uninsured, they may utilize a part of the medical safety-net (such as emergency rooms), at which point researchers may observe their utilization via hospital electronic medical records. Electronic dental records can also be obtained from practices, but 1) there is variation in what record-keeping software is used across offices; 2) dental offices tend to be small business endeavors, and thus the administrative costs of making data accessible to researchers may be quite large; and 3) the cost involved in making claims data from disparate dental practices comparable and obtaining enough data to create a comprehensive view of the market or make meaningful comparisons between practices may be insurmountable for individual researchers. As a
result, the difficulty of obtaining data on the privately insured, publicly insured, and the uninsured has curtailed the ability of researchers to fully characterize the nature of the dental care market, as has been done in the medical care market.

3.2. Relevance of Dental Practices to Primary Care Practices

Studying the impact of demand fluctuations on dental practices may provide some insight into the impact of demand fluctuations on primary care practices. Though there has been literature on how providers and clinical facilities respond to sudden fluctuations in demand, there has been little attention to how primary care facilities respond to sudden demand shocks due to the increased ability of primary care providers to schedule care for later, or push emergencies outside of the primary care clinic.

Instead, the majority of the literature focuses on cases where care cannot be delayed and scheduled for later, due to the acuity of cases seen and the risk of severe consequences to the patient without care. This is in contrast to the literature on demand shocks in settings where facilities are at capacity but cannot turn away patients when they come through the doors, such as for emergency admissions or inpatient settings with acute admissions. This is because the demand fluctuations that take place in a short period of time (due to the severity of cases seen and the inability to turn away patients or reschedule them for later care) differ conceptually from demand fluctuations that can be accommodated and spread out via scheduling. For instance, Evans and Kim (2006) find that when there are weekend surges in hospital admissions on patient outcomes when hospital staff levels are pre-determined, length of stay declines and the probability of subsequent readmission increases, but this focuses specifically on weekend surges where cases are more likely to be acute and less likely to be delayed for treatment later in the week due to risk of severe health consequences to the patient without care. In contrast, Cook et al. (2012) examines the causal impact of changes in regulation governing the patient/nurse ratio in hospitals on failure to rescue, which reflects a focus on how temporal changes in demand that must be immediately accommodated impacts short-term patient outcomes. It is not likely that the
possibly negative impact of demand on patient outcomes that results from these settings occurs because of changes in treatment decision-making - the focus of these studies primarily are to evaluate or project potential effects of legislation regulating minimum nurse to patient ratios in hospital units, and nurses are limited by their scope of practice in what treatments or tests they can perform.

Examining the dental setting allows a look at exogenous shifts in demand that can be accommodated by scheduling that will likely have a general equilibrium impact on how patients are treated in offices, which is likely to be more similar to the types of demand shocks faced by primary care clinics with an insurance expansion. Dental offices generally do not face dental emergencies, which are more often directed towards hospital emergency rooms and covered by medical insurance. Hence, temporal changes in demand generally do not need to be accommodated in a short period of time, which limits any immediate short-run effects on patient outcomes due to lack of attention or mistakes due to short-run staffing issues. Instead, any increases in market demand faced by dental offices can usually be scheduled over a longer period of time so that the provider is not facing immediate shocks to demand, but can choose how to reallocate their resources given an increase in demand spread out over some period of time. Furthermore, there exists a non-trivial amount of excess capacity in dental offices (Vujicic et al., 2013) - hence, dental offices are less likely to face the sudden stress on resources and manpower such as that would stem from a surge in hospital admissions due to low risk of severe health consequences to patients (due to the nature of most dental conditions and due to extreme dental emergencies being covered by medical insurance and being directed to emergency rooms) and ability to schedule and distribute increases in demand over time.

3.3. Data and Sample Restrictions

Though I remain restricted on my ability to characterize parts of the dental market due to data limitations, I resolve several of the issues mentioned previously, especially those affecting measurement of provider behavior, using a novel source of data to the economics
literature. I use 2008-2014 dental claims from Delta Dental of Michigan, Indiana, and Ohio (DDMI) that traces providers across claims, patients, and years, spanning the majority of its privately insured beneficiaries under employer-sponsored dental plans. A version of this claims database has been used previously in studies of oral health (Heller et al. 2004), of treatment trends (Eklund 1997), and to compare treatment options (Bogacki et al. 2002). However, this is the first time to my knowledge that a comprehensive dental claims database from a large insurer has been used to evaluate the effects of a policy change on treatment behavior.

Delta Dental is one of the top three dental insurance carriers across the United States (the other two are Aetna and MetLife). On a whole, Delta Dental is a nonprofit organization with 39 dental service organizations, which operate in all 50 states, the District of Columbia, and Puerto Rico. Each of its subsidiaries are independent, but overall were expected to account for 28.5% of total industry revenue in 2014 (IBISWorld - Delta financial info.pdf). DDMI, whose claims data I use in this project, primarily operates in Michigan, Indiana, and Ohio, but DDMI also actively operates in Arkansas, Kentucky, New Mexico, North Carolina, and Tennessee. Within DDMI’s main states of business, DDMI and its affiliates held 64.8% market share in the dental insurance industry in 2014, with 4.16 million subscribers. Most of its business is in providing dental coverage through employers. Because premiums are highly proprietary data, I was not able to obtain premium levels for plans, but SNL Peer Analytics reports that DDMI had premiums of $28 per member-month in 2015, while other dental insurers operating in Michigan had an average premium of $316 per member-month, a minimum of $3 per member-month, and a maximum of $1,432 per member month. Though employers with non-disclosure agreements with Delta Dental were excluded from the data, the DDMI data contains more than 4000 employers across 2008-2014 with employees residing in Michigan.

Though the data contains providers and patients across all fifty states, I restrict the analysis to patients and providers in Michigan, the main state of business for Delta Dental of Michi-
gan. This is because I am able to capture a higher percentage of an office’s patients in the data relative to other states, where Delta Dental may have lower penetration among offices. Furthermore, the penetration of this branch of Delta Dental in Michigan is greater than 65% according to SNL Financial (the market share among other states in the data could not be calculated using the SNL Financial Peer Analytics tool), and the probability that a dentist is included in DDMI’s network is much higher in these three states. Together, this decreases the likelihood that new patients who are newly enrolled in Delta Dental plans in practices are switching between insurers (which would imply that the increase in enrollment in DDMI is not reflective of industry trends, but is merely business-stealing) or switching between providers (which would imply that the increase in Delta Dental new enrollment took place among individuals who were previously seeing the dentist while uninsured or while insured under a different insurer). I discuss both of these points further in Sections 3.5 and 4.2. Restricting the analysis to Michigan results in more than 8 million unique enrollees over 81 unique counties.

The data is comprised of an enrollment file containing all beneficiaries enrolled in the employer-sponsored dental plans and claims files for every year between 2008 and 2014. Both types of files contain masked identifiers for providers, beneficiaries, employers, and plans, allowing providers and beneficiaries to be traced over time, and for plan benefit designs to be known across a large set of consumers. This data includes procedure codes, negotiated prices, charges, insurer payments, and out-of-pocket prices paid by patients. The enrollment file also contains beneficiary information, such as age, county of residence, and whether the enrollee is a dependent and of which family, and dental provider information, such as the county of operation. This allows me to 1) identify which subsets of the population are eligible for the dental coverage expansions and 2) define dental markets at the county level.

Tables 2 through 4 contains summary statistics for the Michigan-specific data across enrollees with any dental utilization and across the continuously insured patients (continuously
insured from at least 2008 to 2013), who are the focus of the main office-level analyses. In the full Michigan sample, individuals enrolled in Delta Dental plans are an average of 44.79 years old, which is in line with the average age of the working-age population. To examine how enrollment is distributed across age brackets, I construct age groups to reflect those who are young enough for dependent coverage prior to the dependent coverage expansion and are not directly affected by the expansion (0 to 17 year olds), those who are directly eligible (18 to 26 year olds), those who are not eligible for dependent coverage and likely not young enough to have dependents who are eligible (27 to 33 year olds, generally used in prior literature as a control group for the 18 to 26 year olds), those who are not as comparable to the directly eligible group but younger than retirement age (35 to 64 year olds), and those who are retirement age and above (65 to 84 year olds and above age 85). The majority of individuals are between 35 to 64 years of age (48.29% of the entire population enrolled in Delta Dental in Michigan). Tables 2 reveals that just over half of all unique individuals enrolled in Delta Dental plans are continuously insured in the same plan from at least 2008 to 2013, with a similar age distribution and county demographics as for the entire population of individuals enrolled in Delta Dental plans.\(^3\)

Across the entire population of Michigan enrollees, each individual averages just over two routine visits per year\(^4\), which is the usual recommended minimum frequency of routine dental visits. Though routine procedures are generally covered at 100%, the median yearly out-of-pocket cost across all enrollees is $44.8 and $42 for continuously insured enrollees. Reflecting the average of approximately two routine visits per year, the average expenditure per visit is approximately $24 across all enrollees, as well as across the continuously insured

\(^3\)In 2012, Delta Dental was selected by the UAW Retiree Medical Benefits Trust to administer a preventive dental plan among retirees of Chrysler and General Motors (Delta Dental of Michigan, Ohio, and Indiana, 2011). Retirees were automatically enrolled, but were provided full coverage only for preventive and diagnostic services, emergency palliative treatment, radiographs, and minor restorative procedures (Delta Dental of Michigan, Ohio, and Indiana, 2011). As a result, this was an increase in enrollment that was unrelated to the dependent coverage expansion and specific to Delta Dental, not common across the dental industry. Furthermore, this was a plan that did not mirror typical dental benefit designs in the market and the automatic enrollment of retirees in 2012 was announced to dental professionals prior to the start of enrollment and thus did not constitute a sudden shock to dental offices. To avoid the noise that this change in coverage for retirees lends to the data, I drop individuals of retirement age (over age 65) in the data.

\(^4\)Routine visits are defined as visits where only routine procedures take place.
enrollees. The dental expenditure distribution, much like medical expenditure distributions, have a long right tail, resulting in mean out-of-pocket costs that are more than $100 above the median out-of-pocket costs. This reflects that though dental expenditures with dental coverage generally are low, the lack of catastrophic coverage in dental plans can result in high levels of out-of-pocket spending for some patients. Even among those who are continuously insured over the length of the sample time period with coverage, and have had access to routine and preventive dental care consistently over time, 25% of continuously insured patients incur expenses of more than $143.50 and 5% of continuously insured patients incur expenses of more than $739.60.

Mean approved amounts per year and per visit in the data align closely to the estimated cost of a routine visit based on the fees for the East North Central Division of the United States from the 2013 American Dental Association Survey of Dental Fees discussed in Section 2.3. Using the ADA survey, a single routine visit encapsulating an oral evaluation, a set of bitewing X-rays, fluoride application, and cleaning averaged around $216.23 in total reimbursement and had a high end of $286. In comparison, average yearly approved amounts were $547.69 across all Michigan patients, which divided by the average number of routine visits among patients yields approximately $273.85 per visit. The mean approved amount per visit falls a little under this estimate of the cost of a routine visit with $230.93, but both mean approved amounts fall within the bounds of the cost estimate across the industry for a routine visit. The mean approved amounts for continuously insured patients are comparable as well.

The distribution of plan payment amounts exhibits less variation relative to the out-of-pocket expenditure and total provider reimbursement distributions. Yearly amounts paid to dental providers per patient have a median of $226.7. As expected from the structure of dental insurance plans, the majority of the average reimbursement per visit is borne by the insurer. However, as the expenditure per patient per year increases, increasingly more of the cost is borne by the patient, with the top 1% of patients responsible for more
than 50% of total provider reimbursement per year. This reflects that dental insurance plans offered by Delta Dental, like the majority of dental benefits, primarily cover routine services and catastrophic costs are borne by the patient, presumably until the point to which the costs of care are charged to health insurers or to the public safety net. Despite the ability to charge higher levels of dental expenditure to health insurers for some types of care, this demonstrates that patients may bear significant financial risk from incurring dental expenditures even when covered by dental insurance and health insurance 5.

I initially define markets to be at the county level because the finest geographic level available in the data is the county level for both providers and enrollees and distance to the provider is only available for providers that the enrollee has visited. 91% of observations are to providers within 20 miles of the enrollee’s residence, while the median land area of a U.S. county is 622 square miles, and 76-80% of enrollees in each claim year are seen by providers operating in the same county that the enrollee resides in. As a result, the majority of enrollees are choosing providers that are in the same county. Hence, the county-level shocks approximate the market-level shocks. In the office-level analysis, I refine the market definition using a variation of the Elzinga-Hogarty approach, which allows for a variable office-specific radius to define the market, which leverages the limited data on the travel distance between patients and dental offices available. This is further discussed in Section 4.2.1 for the description of the office-level analyses.

For office-level regressions later on, I impose further sample restrictions at the office-level. First, I restrict to offices that are present for all years used in the analysis (2008-2013) to ensure that treatment behavior is observed in every year for each office. I restrict further to offices comprised of only general dental practitioners and exclude specialists or offices with a mix of generalists and specialists 6. This is because offices that tend to have more than three providers per practice are extreme outliers, and are also more likely to have

5 Because the data covers employer-sponsored dental plans administered by Delta Dental, individuals enrolled in these plans are likely also to have had an offer of health insurance from their employer.

6 The data does not include dental hygienists or dental assistants, as billing is typically done through the dentist(s) in the office.
much larger offices, which skews the results for some of the office-level regressions later on. Furthermore, this removes offices that are likely to be training facilities and dental schools from the data, which are likely to be facing meaningful differences in severity and as a result have significantly different treatment behaviors relative to regular dental clinics. Lastly, to ensure that there are enough patients each year to measure changes in treatment behavior for each office, I exclude offices with fewer than ten continuously insured patients in any year of the analysis. The effect of the sample restrictions are displayed in Table 5. The office-level sample restrictions do not change the composition of the counties included in the analysis very much, though two rural counties fall out of the analysis.

3.4. Delta Dental Relative Reimbursement Rates

To establish that the reimbursement structure of Delta Dental plans aligns with the general payment structure of dental plans discussed in Section 2.3, I do the following: 1) examine the estimated profit of routine visits to the estimated profit of a one-surface cavity filling to establish that there is a general incentive to take on new patients and 2) examine how reimbursement rates for cleanings compare to reimbursements for preventive treatments with a strong base of supporting clinical evidence. This is in lieu of displaying the reimbursement rates for a given set of procedures, which are confidential.

As before, I calculate the total reimbursement of a routine visit from the reimbursement rates of an oral evaluation, a prophylaxis (cleaning), a topical fluoride varnish, and a set of bitewing X-rays (comprised of four radiographic images). Using Michigan Medicaid rates from 2016 for procedures to approximate the underlying cost to dental providers for providing each treatment (conditional on 100% coverage of the procedure, which is the case for routine procedures), I find that the profit from a routine visit averages $102.55, with an upper limit \(^7\) of $138.55, which is generally greater than the estimated profit from a one-surface anterior resin-based composite filling. As a result, providers taking patients from Delta Dental plans have an incentive broadly to take on new patients when possible.

\(^7\)Calculated from the 95th percentile of the reimbursement rate distribution for each procedure.
rather than initiating restorative treatment for an existing patient.

Using the median approved amounts per procedure across claims for enrollees under age 65 in Michigan, Indiana, and Ohio in 2013 seeing in-network providers, I find that fluoride varnish for adults is reimbursed at 44% of the reimbursement for prophylaxis treatment for adults (cleanings), sealants at 58.5%, and silver diamine fluoride at 55%. Using Michigan Medicaid reimbursement rates from 2016 as a proxy for the underlying cost of treatments (other than for silver diamine fluoride, because Michigan Medicaid does not reimburse for silver diamine fluoride treatments) and subtracting costs from the median approved amounts to estimate profit, fluoride varnish brings in 36.5% of the profit for adult prophylaxis treatments and sealants 53.8%. As a result, there is a broad incentive for providers to provide cleanings (the efficacy of which have never been tested systematically in clinical trials or evaluated robustly) over preventive treatments that do have high levels of clinical effectiveness.

As a result, providers taking patients from Delta Dental plans have an incentive broadly to take on new patients when possible, and are broadly disincentivized against providing preventive treatments (such as sealants and silver diamine fluoride and fluoride varnish) with high efficacy in clinical trials and incentivized towards providing treatments with little clinical basis of support (such as cleanings and most restorative treatment). This is consistent with the provider reimbursement structure of dental insurance plans generally discussed in Section 2.3.

3.5. Dependent Coverage Expansion

As part of the Affordable Care Act, the dependent child coverage mandate required that plans and issuers extend coverage to adult children up to age 26. Though this requirement targeted only health plans, and not dental-only plans, many large employers extended dental coverage to children between ages 18 and 26 in 2011 and 2012. This was largely unexpected by providers - this was because in 2010, dental insurers were sure to inform dental providers

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that the dependent coverage expansion in health plans did not apply to dental. For instance, in October 2010, Delta Dental reported to its network of dentists that the new rules for health plans did not apply to them, but that it would be implemented for clients that requested additional dependent coverage for their employees. Similarly, though Aetna was reported to extend dependent coverage in their medical plans early, the dependent coverage expansion was noted to not apply to dental benefits. Other than briefs or news articles in the general press or in newsletters to dentists, underlining that dependent coverage for dental benefits was not required, there was little to no discussion of how the dependent expansion impacted dental plans until 2014 (Vujicic et al. 2014). This is echoed in Figure 2, which displays the year fixed effects from a specification where the log of the number of offices in each county is regressed upon a series of year and county fixed effects. If providers were able to predict an increase in demand in 2011, one way this may appear in the data is more dental office openings during or before the implementation time period (2011-2012). However, Figure 2 shows that between 2008-2012, there was no statistically significant change in the percentage increase in the number of offices or providers per market relative to 2006 levels.

Insurers suggest that the dependent coverage expansion in dentistry was primarily implemented by large employers, due to a desire to mirror the changes in health coverage in dental coverage. Representatives at Delta Dental of Michigan suggest many large employers extended benefits voluntarily to those under age 26 because of union action - unions saw that health coverage was being extended to dependents under age 26, and wanted these changes to be applied also to dental coverage. Claim administrators for the University of Pennsylvania’s (UPenn) dental plans also concur with this interpretation of events, and all dental plans offered to UPenn faculty, staff, and students were also required to extend benefits to those under age 26. Results from the Delta Dental claims data concur with this interpreta-

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8The increase in 2013-2014 may have come as a belated reaction to the increase in dental coverage and the resulting increase in market demand for dental services from 2011 and 2012, and can be interpreted as either more providers graduating in 2013 and 2014 and opening their offices, or providers who were previously partners or practicing in an office with a group of dentists breaking off and opening their own practices.
tion of events - I detect that the dependent coverage expansion was primarily implemented by large employers (more than 100 employees at least). Using the Delta Dental enrollment file, I regressed the log of the number of 18-26 year old dependents (the target group of the 2011 dependent expansion) in each plan on a series of year, plan, and employer fixed effects with robust standard errors. I carry out this regression for each employer size size (under 100 employees, 101-500 employees, 501-1000 employees, 1001-5000 employees, and 5000+ employees) and map the year coefficients. Table XXX restricts attention to plans that are present in the data starting at least from 2007 and continuing for every year up until 2014, though results including all plans in the data are similar (not included here). The size of the effect ranges between a 10-20% increase in 2011 after a period of little to no growth in enrollment among 18-26 year old dependents between 2007-2010. There appears to be delayed implementation of the dependent expansion among some firms and plans, which Delta Dental representatives agreed with in informal interviews, leading to further gains in enrollment among the target group of dependents in later years (2012-2014), leading to a total increase of 30-40% in the number of 18-26 year old dependent enrollees among plans in 2014 relative to 2007 baseline levels.

3.6. Replicating Earlier Industry-Level Analyses

The dependent coverage expansion was not isolated to Delta Dental, but occurred across multiple insurers. The first papers reporting on a possible dependent coverage expansion in dental insurance were Vujicic et al. (2014) and Shane and Ayyagari (2015). These estimated the size of the dependent coverage expansion using two different sources of survey data, and find that the increase in enrollment among young adults between ages 19-26 years old has been between 5.6 and 6.9 percentage points relative to adults above the 26-year-old dependent coverage age limit. This was followed later by the IBISWorld 2016 Dental Industry report (Curran, 2016), which writes that “[an] uptick in the number of children with dental benefits, coupled with more young adults (i.e. individuals aged 19 to 25) having private dental benefits, has provided a boon to the industry”. As a result, the dependent
coverage expansion was not isolated to a single insurer, but was an industry-wide trend.

Upon carrying out a similar analysis to Vujicic et al. (2014) and Shane and Ayyagari (2015), I find a percentage increase in enrollment among 20 to 24 year olds relative to a control group that is very close to their estimates of 5.6 to 6.9 percentage points. I do this by looking at the percentage change in enrollment over time relative to a base year of 2008, and compare changes in enrollment for 20 to 24 year olds relative to 30 to 34 year olds. Formally, this is done by implementing the following regression:

\[
\log(\text{Enrolled}_{act}) = \beta_0 + \beta_1(18\text{-}26\text{ year olds}_a) + \alpha \log(\text{Pop}_{act}) + \psi_a + \eta_c + \gamma_t + \epsilon_{act}
\]

where \(a\) denotes the age group, \(c\) the county, and \(t\) the year. The coefficients of interest are the \(\beta_t\), which maps the percentage increase in enrollment among 20-24 year olds relative to 2007 and in comparison to 30 to 34 year olds. I use 20 to 24 year olds and 30 to 34 year olds instead of 18 to 26 and 27 to 33 year olds as in Vujicic et al. (2014) and Shane and Ayyagari (2015) to control for time-variant changes in the size of the population of each age group per county, which is only possible using the county characteristics available for five year age bands. I exclude 25 to 29 year olds in the analysis because this age group has a mix of individuals who are and are not eligible for the expansion (includes both those who are below and above age 26). Because the 30 to 34 year olds are too old to be eligible for the dependent expansion, but are closest in age without being eligible to the directly eligible group (20 to 24 year olds), the 30 to 34 year olds serve as a control group to net out changes in enrollment that may be shared across age groups over time. The \(\beta_t\) coefficients along with 95% confidence intervals are mapped in Figure 3. In years prior to the expansion (2008 to 2010), there is no statistically significant difference in the percentage increase in enrollment each year between the treatment (20 to 24 year olds) and control (30 to 34 year olds) groups. However, there is a small, statistically insignificant percentage increase in enrollment among 20 to 24 year olds relative to 30 to 34 year olds.
in 2011, which then becomes statistically significant and sizable in 2012 and 2013. This is primarily because, according to discussions with insurers, it took time for the dependent expansion in dental insurance to be implemented. By collapsing $\beta_t$ into a post-expansion dummy equal to one for 2011 and the years after, and zero otherwise, I find that there is a 7.3% increase in enrollment among 20 to 24 year olds relative to 30 to 34 year olds in the post-implementation period relative to the pre-implementation period. The 95% confidence interval for this coefficient estimate contains the values estimated in Vujicic et al. (2014) and Shane and Ayyagari (2015); hence, the increase in Delta Dental enrollment among those eligible for the expansion relative to those ineligible is similar to estimates of the increase in dependent enrollment for the entire industry, based on survey data.

3.7. Conclusion

To conclude, the dental market is a useful setting in which to study the impact of insurance expansions on provider behavior because private insurance expansions are likely to have a direct impact on access and utilization of dental care, leading to substantial office-level demand shocks, and because dental providers, like medical providers, have incentive and ability to induce demand without detection by both patients and insurers. Furthermore, much of the literature examining how demand fluctuations impact care delivery focuses upon care that cannot be delayed and provides little insight on how non-emergency care delivery responds to temporal changes in demand. Hence, examining the impact of insurance expansions on dental practices may provide some insight into whether there are general equilibrium changes in how patients are treated across offices that do not provide emergency care (i.e. primary care clinics).

Using 2008-2013 Delta Dental of Michigan data, I find that the structure of reimbursements in Delta Dental plans mirror the structure of reimbursements in the general dental industry, discussed in Chapter 2, and that there is an incentive to take on new patients over inducing demand.
Furthermore, the size of the dependent expansion in the dental market estimated in the Delta Dental data closely matches the estimated size found in prior papers for the entire dental industry.
## 3.8. Tables and Figures

<table>
<thead>
<tr>
<th></th>
<th>All</th>
<th>Continuously Insured</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong># Unique Individuals</strong></td>
<td>8882347</td>
<td>4384512</td>
</tr>
<tr>
<td><strong>Avg # Routine Visits Per Individual</strong></td>
<td>2.03492</td>
<td>2.049801</td>
</tr>
<tr>
<td><strong># Unique Plans</strong></td>
<td>4023</td>
<td>1681</td>
</tr>
<tr>
<td><strong>Age</strong></td>
<td>44.79 (22.06)</td>
<td>43.83 (21.93)</td>
</tr>
<tr>
<td><strong>2014 Median Household Income of Area of Residence</strong></td>
<td>51855.6 (10091.0)</td>
<td>52065.5 (10233.2)</td>
</tr>
<tr>
<td><strong>Unemployment Rate</strong></td>
<td>10.22 (2.808)</td>
<td>10.15 (2.831)</td>
</tr>
<tr>
<td><strong>Age Distribution in 2011</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-17</td>
<td>18.26</td>
<td>18.64</td>
</tr>
<tr>
<td>18-26</td>
<td>10.09</td>
<td>12.90</td>
</tr>
<tr>
<td>27-33</td>
<td>6.30</td>
<td>8.45</td>
</tr>
<tr>
<td>35-64</td>
<td>48.29</td>
<td>47.61</td>
</tr>
<tr>
<td>65-84</td>
<td>15.46</td>
<td>11.16</td>
</tr>
<tr>
<td>85+</td>
<td>1.59</td>
<td>1.25</td>
</tr>
<tr>
<td><strong>Total</strong></td>
<td>100.00</td>
<td>100.00</td>
</tr>
</tbody>
</table>

Note: Summary statistics are from the full dataset between the years 2008-2013 obtained from Delta Dental of Michigan. This incorporates Michigan only. Due to legal restrictions, some employers were removed from the data due to non-disclosure agreements. The continuously enrolled are defined to be enrollees who have been enrolled in the same Delta Dental plan from at least 2008 to 2013. The sample is limited to those over age 0 and under age 100.
Table 3: Distribution of Yearly Expenditure Per Patient

<table>
<thead>
<tr>
<th></th>
<th>All Patients</th>
<th></th>
<th>Continuously Insured</th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Approved Amt</td>
<td>Plan Amt</td>
<td>OOP</td>
<td>Approved Amt</td>
</tr>
<tr>
<td>Mean</td>
<td>547.6924</td>
<td>344.4948</td>
<td>166.5862</td>
<td>542.9241</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>716.6804</td>
<td>349.9029</td>
<td>478.6907</td>
<td>745.4717</td>
</tr>
<tr>
<td>Percentiles</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1%</td>
<td>54</td>
<td>0</td>
<td>0</td>
<td>50</td>
</tr>
<tr>
<td>5%</td>
<td>93</td>
<td>24.5</td>
<td>0</td>
<td>88</td>
</tr>
<tr>
<td>25%</td>
<td>178</td>
<td>125.55</td>
<td>0</td>
<td>167</td>
</tr>
<tr>
<td>50%</td>
<td>292</td>
<td>226.7</td>
<td>44.8</td>
<td>283</td>
</tr>
<tr>
<td>75%</td>
<td>621</td>
<td>404.8</td>
<td>147.4</td>
<td>620</td>
</tr>
<tr>
<td>95%</td>
<td>1821</td>
<td>1061.1</td>
<td>729.65</td>
<td>1847</td>
</tr>
<tr>
<td>99%</td>
<td>3089</td>
<td>1635</td>
<td>1820</td>
<td>3099</td>
</tr>
</tbody>
</table>

Note: Summary statistics are from the full dataset between the years 2008-2013 obtained from Delta Dental of Michigan. This incorporates Michigan only. Due to legal restrictions, some employers were removed from the data due to non-disclosure agreements. The continuously enrolled are defined to be enrollees who have been enrolled in the same Delta Dental plan from at least 2008 to 2013. The sample is limited to those over age 0 and under age 100.
### Table 4: Distribution of Average Expenditure Per Visit Per Patient

<table>
<thead>
<tr>
<th>Percentiles</th>
<th>All Patients</th>
<th></th>
<th></th>
<th>Continuously Insured</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Approved Amt</td>
<td>Plan Amt</td>
<td>OOP</td>
<td>Approved Amt</td>
<td>Plan Amt</td>
<td>OOP</td>
</tr>
<tr>
<td>Mean</td>
<td>230.9312</td>
<td>150.458</td>
<td>64.85758</td>
<td>237.143</td>
<td>151.6676</td>
<td>66.58484</td>
</tr>
<tr>
<td>St. Dev.</td>
<td>286.4553</td>
<td>129.734</td>
<td>207.7628</td>
<td>311.4913</td>
<td>137.6369</td>
<td>232.2998</td>
</tr>
<tr>
<td>1%</td>
<td>55</td>
<td>0</td>
<td>0</td>
<td>53</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>5%</td>
<td>82</td>
<td>17.8</td>
<td>0</td>
<td>81</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>25%</td>
<td>117.5</td>
<td>87.66666</td>
<td>0</td>
<td>118</td>
<td>84.9</td>
<td>0</td>
</tr>
<tr>
<td>50%</td>
<td>152</td>
<td>120</td>
<td>24.06667</td>
<td>155</td>
<td>120</td>
<td>24</td>
</tr>
<tr>
<td>75%</td>
<td>242</td>
<td>170.65</td>
<td>64</td>
<td>249</td>
<td>173.3333</td>
<td>65</td>
</tr>
<tr>
<td>95%</td>
<td>612.5</td>
<td>372.8</td>
<td>246.25</td>
<td>641</td>
<td>388.8667</td>
<td>259.3333</td>
</tr>
<tr>
<td>99%</td>
<td>1235.333</td>
<td>678</td>
<td>660.6667</td>
<td>1291.5</td>
<td>728</td>
<td>685.65</td>
</tr>
</tbody>
</table>

Note: Summary statistics are from the full dataset between the years 2008-2013 obtained from Delta Dental of Michigan. This incorporates Michigan only. Due to legal restrictions, some employers were removed from the data due to non-disclosure agreements. The continuously enrolled are defined to be enrollees who have been enrolled in the same Delta Dental plan from at least 2008 to 2013. The sample is limited to those over age 0 and under age 100.
Table 5: Office-Level Sample Restrictions

<table>
<thead>
<tr>
<th></th>
<th>Michigan Only Balance</th>
<th>General Only ≤3 Providers</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td># Offices</td>
<td>3508</td>
<td>2506</td>
<td>2375</td>
</tr>
<tr>
<td># Counties</td>
<td>80</td>
<td>79</td>
<td>78</td>
</tr>
<tr>
<td>Avg # Providers Per Office</td>
<td>1.56</td>
<td>1.21</td>
<td>1.21</td>
</tr>
<tr>
<td>Avg Rural-Urban Classification</td>
<td>2.17</td>
<td>2.19</td>
<td>2.21</td>
</tr>
<tr>
<td>Avg Median HH Income (2014)</td>
<td>$52,652.63</td>
<td>$52,673.51</td>
<td>$52,666.77</td>
</tr>
<tr>
<td>Avg Unemployment Rate</td>
<td>9.88%</td>
<td>11.29%</td>
<td>11.28%</td>
</tr>
</tbody>
</table>

Figure 2: Percentage Change in # Offices Per County Over Time Relative to 2008

Notes: This figure displays the year fixed effects from a regression of the log of the number of offices in each county on a series of year and county fixed effects. 90% confidence intervals are given by the bars. Standard errors are clustered at the county level.
<table>
<thead>
<tr>
<th>CDT Code</th>
<th>Procedure Description</th>
<th>Relative Reimbursement</th>
</tr>
</thead>
<tbody>
<tr>
<td>D1206, D1208</td>
<td>Topical fluoride varnish - adult</td>
<td>44.1%</td>
</tr>
<tr>
<td>D0274</td>
<td>Bitewings - four radiographic images</td>
<td>70.6%</td>
</tr>
<tr>
<td>D2330</td>
<td>Resin-based composite - one surface, anterior</td>
<td>164.7%</td>
</tr>
<tr>
<td>D2391</td>
<td>Resin-based composite - one surface, posterior</td>
<td>176.5%</td>
</tr>
<tr>
<td>D1206</td>
<td>Topical fluoride varnish</td>
<td>44.1%</td>
</tr>
<tr>
<td>D1351</td>
<td>Sealant - per tooth</td>
<td>58.5%</td>
</tr>
<tr>
<td>D2940</td>
<td>Protective restoration (ITR)</td>
<td>110.3%</td>
</tr>
<tr>
<td>D1354</td>
<td>Silver diamine fluoride</td>
<td>0.0%</td>
</tr>
</tbody>
</table>

The relative reimbursement rate for each procedure is calculated by the median approved amount for the procedure, divided by the median approved amount for an adult prophylaxis treatment. Median approved amounts are taken from claims among enrollees of Delta Dental of Michigan, Indiana, and Ohio in 2013, who are seeing in-network providers for enrollees under age 65. The median approved amounts are taken across multiple employer-sponsored plans administered by Delta Dental of Michigan, Indiana, and Ohio. The median approved amounts are confidential, therefore I provided the relative reimbursement ratios.
Table 7: Dependent Dental Enrollment: Increases Among Employers by Size of Employer (Plan-Level Regressions)

<table>
<thead>
<tr>
<th>Log(# 18-26 yo Enrollees)</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>&lt;100</td>
<td>-0.00798</td>
<td>0.0219**</td>
<td>0.0411*</td>
<td>0.00993</td>
<td>-0.103</td>
</tr>
<tr>
<td>(0.0140)</td>
<td>(0.0108)</td>
<td>(0.0231)</td>
<td>(0.0499)</td>
<td>(0.141)</td>
<td></td>
</tr>
<tr>
<td>101-500</td>
<td>-0.0176</td>
<td>0.0145</td>
<td>0.0506</td>
<td>0.0173</td>
<td>-0.118</td>
</tr>
<tr>
<td>(0.0188)</td>
<td>(0.0150)</td>
<td>(0.0368)</td>
<td>(0.0491)</td>
<td>(0.146)</td>
<td></td>
</tr>
<tr>
<td>501-1000</td>
<td>-0.0559**</td>
<td>0.0106</td>
<td>0.0341</td>
<td>0.0200</td>
<td>-0.0910</td>
</tr>
<tr>
<td>(0.0227)</td>
<td>(0.0179)</td>
<td>(0.0457)</td>
<td>(0.0524)</td>
<td>(0.152)</td>
<td></td>
</tr>
<tr>
<td>1001-5000</td>
<td>-0.0304</td>
<td>0.0946***</td>
<td>0.177***</td>
<td>0.176***</td>
<td>0.0769</td>
</tr>
<tr>
<td>(0.0253)</td>
<td>(0.0204)</td>
<td>(0.0580)</td>
<td>(0.0555)</td>
<td>(0.157)</td>
<td></td>
</tr>
<tr>
<td>5000+</td>
<td>-0.0265</td>
<td>0.123***</td>
<td>0.245***</td>
<td>0.260***</td>
<td>0.184</td>
</tr>
<tr>
<td>(0.0280)</td>
<td>(0.0235)</td>
<td>(0.0684)</td>
<td>(0.0585)</td>
<td>(0.159)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.0275</td>
<td>0.158***</td>
<td>0.273***</td>
<td>0.333***</td>
<td>0.243</td>
</tr>
<tr>
<td>(0.0298)</td>
<td>(0.0234)</td>
<td>(0.0676)</td>
<td>(0.0635)</td>
<td>(0.161)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>-0.0842***</td>
<td>0.147***</td>
<td>0.263***</td>
<td>0.368***</td>
<td>0.263</td>
</tr>
<tr>
<td>(0.0308)</td>
<td>(0.0257)</td>
<td>(0.0719)</td>
<td>(0.0668)</td>
<td>(0.174)</td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>2.261***</td>
<td>3.894***</td>
<td>4.823***</td>
<td>5.823***</td>
<td>7.419***</td>
</tr>
<tr>
<td></td>
<td>(0.0184)</td>
<td>(0.0153)</td>
<td>(0.0426)</td>
<td>(0.0472)</td>
<td>(0.134)</td>
</tr>
<tr>
<td>Observations</td>
<td>6,388</td>
<td>4,538</td>
<td>1,005</td>
<td>1,149</td>
<td>460</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.004</td>
<td>0.054</td>
<td>0.094</td>
<td>0.199</td>
<td>0.108</td>
</tr>
<tr>
<td>Number of Plans</td>
<td>841</td>
<td>571</td>
<td>126</td>
<td>145</td>
<td>59</td>
</tr>
<tr>
<td>Plan FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Employer FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
</tr>
<tr>
<td>Level Mean</td>
<td>15.43</td>
<td>68.31</td>
<td>177.8</td>
<td>572.3</td>
<td>3135</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Note: This table presents the increase in dependent coverage (measured by the log of the number of 18 to 26-year-old individuals in each plan) in each plan by employer size, for plans that are in the data for all years of the analysis (2007-2014). Results are comparable for the full, unbalanced sample.
Figure 3: Percentage Change in Enrollment Among 20-24 Year Olds vs. 30-34 Year Olds from 2009-2013, Relative to 2008

Notes: This figure maps the coefficients on the interaction between the treatment dummy (equal to one for the 20 to 24 year old age group, and zero for the 30 to 34 year old age group) to examine the percentage increase in enrollment among 20-24 year olds relative to 2007 and in comparison to 30 to 34 year olds. County and year fixed effects are included, as well as controls for the population size for each age group in each county. 95% confidence intervals are given by the bars. Standard errors are clustered at the county level.
CHAPTER 4 : Analysis

4.1. Variation in the Size of the Dependent Expansion and Market-Level Effects

Though it is possible to examine how enrollment changes before and after the implementation of the dependent coverage expansion, leveraging variation in the size of the dependent expansion across markets allows one to control for changes over time across counties and markets that may be unrelated to the dependent expansion. Furthermore, measuring changes in Delta Dental enrollment before and after the timing of the expansion may only speak to what is happening within Delta Dental plans, instead of industry-wide trends. For instance, the increases in enrollment may only be experienced within Delta Dental, and these increases would not impose a large shock to dental offices, because patients are merely switching insurers.

To avoid capturing Delta Dental-specific changes in enrollment, I look at how a key industry-wide predictor of the size of the dependent expansion in a county affects Delta Dental enrollment. This industry-wide predictor of the size of the dependent expansion in a county is the number of newly eligible individuals in the county in 2011. Controlling for differences in population sizes, a county with a larger proportion of individuals in the population that are newly eligible for dependent coverage will be subject to larger increases in dental coverage rates from the expansion. The ideal measure of the proportion of individuals who are newly eligible for the dependent expansion in the county would be the proportion of 18 to 26 year olds without dental insurance in the overall population, but this data is not collected by any agencies. In lieu of this, using the proportion of 18 to 26 year old individuals in the market (with or without dental insurance) would be a fair approximate, because this population is less likely to have had an offer from an employer for dental insurance, and also faces significant cost barriers to purchasing individual dental plans and to seeing the dentist out-of-pocket without insurance (Nasseh et al. 2015). However, there is no dataset that the author knows of that records the number of 18 to 26 year olds in each county -
county population datasets typically separate population by five-year age bands. Instead, I use the ratio of 20 to 24 year olds in each county in 2011 to predict the initial size of the expansion in each market, which captures the majority of the age group of interest without capturing individuals in other age groups that are not directly eligible for the dependent coverage expansion. For brevity, I call this the "eligible ratio".

I use a difference-in-differences specification, allowing the treatment dosage to vary, where the treatment dose is the size of the eligible ratio, which controls for time-invariant differences between counties that have a higher and lower eligible ratio. Figure 4 is the distribution of the eligible ratio across counties, and shows that there is a large amount of variation across Michigan counties in the ratio of eligibles in county populations. The standardized normal distribution in Panel (b) of Figure 4 shows that some counties may be up to as much as four standard deviations from the mean eligible ratio, where some counties have more than 20% of their population under age 65 between ages 20 and 24.¹

To evaluate the parallel trends assumption inherent to difference-in-differences analysis, I regress the log of DDMI coverage rates by age group (calculated by taking the number of individuals enrolled in DDMI, divided by the size of the county subpopulation for each age group) on the interaction of the main treatment variable, the log of the eligible ratio in the county, with year dummies. The resulting regression specification is the following:

$$\log(\text{Covg Rate}_{act}) = \beta_0 + \alpha_t \log(\text{Eligible Ratio}_c) + \beta_1 X_{ct} + \eta_c + \gamma_t + \epsilon_{act}$$

where $a$ is the age group, $c$ the county, and $t$ the year. I use the log of the eligible ratio (which is time-invariant) to take into account that the distribution of the eligible ratios is

¹The county with 24.88% of its under 65 population between ages 20 and 24 in 2011 is Isabella County, which the 2013 American Community Survey reports has a median age of 26 and has 29.7% of its total native born population between ages 18 and 24. The county with the second highest eligible ratio is Houghton County with 17.4% between ages 20 and 24, which the 2013 American Community Survey reports has 19.2% of its native born population between ages 18 and 24. Washtenaw County, where the University of Michigan - Ann Arbor resides, ranks 6th highest among Michigan counties in the eligible ratio with 13.7% of the population under age 65 between ages 20 and 24.
skewed, and the log of the coverage rates to allow for a percentage interpretation. County and year fixed effects (η c and γ t) are included to account for time-invariant differences between counties and changes in coverage rates over time that are shared across counties. To account for variation over time in market conditions, I include variables in X ct such as the log of the size of the population without any form of insurance (between ages 18-64, and under age 19), the unemployment rate, and the number of dental offices per county. This is important because, for instance, changes in health insurance coverage in a county could also impact take-up of dental insurance, and this is variation that is not directly related to the dental dependent coverage expansion. Likewise, changes in unemployment over time would affect the proportion of the population that has access to employer-sponsored insurance plans. I report also the results using the log of the number of people enrolled in each age group in Delta Dental as the dependent variable with the log of the size of the population of the age group in the county as an additional independent variable for robustness and additional interpretation. The goal of this analysis is to test for 1) no statistically significant differences in coverage rates between counties with varying levels of the eligible ratio prior to the implementation of the expansion; 2) a statistically significant increase in coverage rates among age groups that we expect to be affected by the expansion after the dependent expansion in 2011-2013; and 3) no statistically significant change in coverage rates among age groups not expected to be affected by the expansion in 2011-2013.

The age groups examined are the following: 1) ages 65 and younger, 2) 0-14 year olds, 3) 15-19 year olds, 4) 20-24 year olds, 5) 25-29 year olds, 6) 30-34 year olds, and 7) 35-64 year olds. Though 25 to 29 year olds include 25 year olds that may be eligible for the dependent coverage expansion, I examine five-year age bands because the denominator of the coverage rate dependent variable is the size of the county population in the age group, and the county population variables are available only in five-year age bands. Though I also run the regressions using log of the enrollment in Delta Dental for each age group as the dependent variable, this version of the regressions still include county population in the age group as an independent variable to account for changes in county population over time,
and to make the results comparable to those from the coverage rate regressions.

A priori, the primary effects should be concentrated among age groups directly impacted by the dependent coverage expansion, the 15-19 and 20-24 year olds, with limited effects on the 25-29 year olds and no effect on the 30-34 year olds. There may be effects among 0-14 year olds and 35-64 year olds if the implementation of the dependent coverage expansion caused families overall to be aware of the availability of both dental coverage for those who were too young to have been eligible for the expansion before and after implementation and of dental coverage in general for their families.

Figure 5 shows that prior to 2011, there is no statistically significant relationship between coverage rates and the size of the eligible ratio relative to 2007, for the overall dental insurance coverage rate among those under age 65 and by age subgroup. Starting from 2011, there is a statistically significant percentage increase in coverage rates for the overall population under age 65, which is primarily from percentage increases in coverage from those that are most likely to be impacted by the dependent expansion (15-19, and 20-24 year olds) and those that may be impacted via an increase in awareness of availability of dependent dental coverage (0-14 year olds and 35-64 year olds). There is no statistically significant percentage increase in coverage among those ages 25 to 34, which are the age group that we expected no to little effect from.

Table 8 collapses the year coefficients on the eligible ratio into a post-implementation coefficient, where the eligible ratio has an impact on coverage rates only in 2011 and the years following. Over individuals under age 65, a 100% increase in the eligible ratio for a county is associated with a 9% increase in the coverage rate, all else fixed (Column 1). Breaking down by age group, the largest effects in the percentage increase in coverage rate come from the primary age groups of interest, 15-19 and 20-24 year olds, where a 100% increase in the eligible ratio for a county is associated with a 11.2% and a 10.5% increase in coverage rate respectively. There is also a somewhat smaller effect on the percentage change in coverage rates for 35-64 year olds after the expansion is implemented, of 8.51% in response to a 100%
increase in the eligible ratio.

To translate the coefficients in Table 8 to more easily interpretable numbers, I calculate the standardized coefficients in Table 10, which are then used to estimate the increase in enrollees per market on average and the potential size of the increase in number of patients per office. A one standard deviation increase in the eligible ratio from the mean implies a 2.82% increase in the coverage rate among those under age 65 on average across counties in the sample. On average, this implies a 0.7 percentage point increase in DDMI coverage. Because the average size of the population under 65 years of age is 106,596 in the sample, this represents roughly an increase of 746 Delta Dental enrollees. Because there are approximately 2000 general offices in Michigan and 83 counties, this is approximately 31 new Delta Dental enrollees per practice, which predicts up to a 9.2% increase in the number of patients under age 65 for the average office. Hence, not only is the market-level shock from the dependent expansion substantive, but the office-level shock (conditional on offices being responsive to market-level shocks) is substantive as well.

Table 9 gives some insight into why 35-64 year olds are increasing substantially in coverage by examining the effect on the percentage increases in enrollment from an increase in the eligible ratio. Though Table 8 found no statistically significant impact on coverage rates among 0 to 14 year olds, there was still a statistically significant increase when examining the percentage change in enrollment, where a 100% increase in the eligible ratio is associated with a statistically significant 13% average increase in the number of 0 to 14 year olds enrolled in Delta Dental plans. In fact, the largest percentage increases in enrollment numbers are found among 0-14 year olds, with smaller percentage increases among 15-19, 20-24, and 35-64 year olds. However, this is still consistent with Table 8, primarily because though the percentage gain in number of 0 to 14 year olds was statistically significant, this was a small change in coverage rates among the 0 to 14 year old population across counties. Likewise, the gain in coverage among 20 to 24 year olds, though a smaller percentage increase in enrollment, implied a larger impact on the overall coverage rate in a county
for this population. Because both 0-14 and 35-64 year olds are increasing in enrollment in response to the dependent expansion, this suggests that there may have been spillovers onto families with dependents that were too young to be directly impacted by the expansion, simply because of an increase in information about dental dependent coverage.

To rule out the possibility that there was not a concurrent change in the market affecting enrollment of 35 to 64 year olds at the same time, which would have increased enrollment among both parents and non-parents, I split up the population in Column (7) of Table 9 to separate parents of dependents under age 26 from those who are enrolled without dependents. Enrollees are deemed to be parents if they have dependents who are enrolled in Delta Dental, and non-parents otherwise. I further split the parents by the age of their dependents - those with dependents under age 17, who are too young to be directly impacted by the expansion, and those with dependents between ages 18 and 26. Results are reported in Table 12. Overall, increases in enrollment among 35 to 64 year olds stem only from parents of dependents, where a 100% increase in the eligible ratio will yield a 9.05% increase in enrollment among parents of dependents between ages 0 to 26, who are themselves between ages 35 and 64 (Column 1). In contrast, there is no statistically significant change in non-parental enrollment for those between ages 35 to 64 in response to the dependent expansion implementation (Column 4). Furthermore, the increases in parental enrollment are concentrated among parents with dependents between ages 0 to 17, with no change in parental enrollment for those with dependents between ages 18 to 26. The results from Table 12 along with the percentage increase in enrollment among those between ages 0 to 14 from Table 9 suggest that there were indeed unintended and unanticipated increases in enrollment from the dependent expansion from families with dependents that were too young to be directly impacted by the expansion.

The spillovers in enrollment among families with dependents that are too young to be directly eligible for the dependent expansion are non-trivial. I use the standardized coefficients for Table 9, contained in Table 11 to calculate the increase in enrollment from each
age group due to a one standard deviation increase in the county eligible ratio. Though the percentage increase in coverage for 35 to 64 year olds is smaller than the percentage increases among 15-19 and 20-24 year olds, the 35 to 64 year olds represent a large share of enrollment in Delta Dental, with 51.2% of total enrollment under age 65 coming from this group. In comparison, 15 to 19 year olds and 20 to 24 year olds represent only 6.95% and 6.28% of total enrollment under age 65. As a result, 50.3% of the increase in enrollment from the expansion comes from the 35 to 64 year old group on average.

The spillovers are an important factor in how heavily offices are impacted by the dependent expansion. This is because in general, offices have difficulty capturing individuals between ages 21 to 34, who face the most significant cost barriers to care (Nasseh et al. 2015). Furthermore, individuals in the target age group between ages 18 to 26 year olds tend to travel further to dental offices, presumably because they are living away from home or away at school. Figure 6 displays this, showing that 18 to 26 year olds tend to travel further to the dentist on average, with much wider variation in distance than other age groups. As a result, whether the shock at the office-level from the dependent expansion is sizable will heavily depend on whether the increase in enrollment among 35 to 64 year olds translates to an increase in the number of patients among 35 to 64 year olds. Without an increase among 35 to 64 year olds, and only an increase among the younger age groups, we can expect only up to a 4.5% increase in the number of patients per office.

By using an industry-wide predictor for the dependent expansion, the county-level analyses suggest that the increases in coverage and enrollment were not merely increases in Delta Dental enrollment or market share, but an increase in overall industry enrollment. Furthermore, the increases in coverage stemmed primarily from increases in the target age groups (15 to 19 and 20 to 24 year olds), with spillover effects on coverage for individuals between ages 35 to 64 who are parents of those too young for the expansion (ages 0 to 17).

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2The calculation is conducted via the standardized coefficients for Table 9, where a one standard deviation increase in the eligible ratio yields a 2.59% increase in enrollment for those under age 65. This then yields an increase of 3,593 (=0.0259*138,729) enrollees under age 65, with (=0.0251*72,038) enrollees coming from the 35 to 64 year old age group.
In contrast, there was no increase in enrollment in age groups that should not have been affected, primarily the 25 to 29 year olds, the 30 to 34 year olds, and 35 to 64 year old adults that were not parents. The market-level analysis suggest that the increase in the number of patients in each office could be as much as 9.2% with a one standard deviation increase in the eligible ratio.

4.1.1. Falsification Test

I also implement a falsification test to show that the eligible ratio is a valid proxy for the size of the dependent expansion in each county by using the ratio of the population that is between ages 30 to 34 in each county. The falsification test carries out the same analyses as in Tables 8 and 9, but simply replacing the main regressor of interest with the false proxy, the ratio of the population in the 30 to 34 age bracket, comprised of individuals who are not eligible for the dependent expansion, nor likely to have any dependents directly impacted by the dependent expansion.

Figure 7 displays the distribution of the ratio of 30 to 34 year olds in the population across counties. As previously, there is a substantial amount of variation across counties, but the distribution is more evenly spread across counties and approximates a normal distribution more than the ratio of the 20 to 24 year olds. Relative to the distribution of the ratio of 20 to 24 year olds in the population under age 65 across counties, there are more counties to the left of the mean, whereas the distribution of the eligible ratio had a long right tail.

Figure 8 implements the parallel trends test carried out previously using the eligible ratio in Figure 5. Unlike Figure 5, the parallel trends assumption is not fulfilled, with statistically significant differences between counties with high and low ratios of 30 to 34 year olds in the years preceding the dependent expansion (2009 and 2010) relative to the base year of 2008. This is because the proportion of 30 to 34 year olds in a county is likely to reflect differences in employment between counties (such as unemployment rate, or different industries) and these differences will affect both the likelihood that dental insurance is
offered to individuals living (and/or working) in a county and the likelihood of take-up of an offer of dental insurance. Hence, there are unobserved differences between counties with high and low ratios of 30 to 34 year olds in the population driving differential pre-trends in dental insurance enrollment.

In the context of non-parallel trends, the dosage difference-in-differences analysis is not valid, but the regression coefficients for the falsification test are given in Tables 13 and 14 for the sake of comparison. There is no statistically significant percentage change found for coverage rates and enrollment among all age groups from being in a county with a higher "non-eligible ratio" (the ratio of 30 to 34 year olds in the population) in the post-implementation period of the dependent expansion.

As a result, this supports the argument that the eligible ratio (the ratio of 20 to 24 year olds in the county population under age 65) is a valid proxy for the size of the dependent expansion.

4.2. The Effect of a Market Expansion on Office Load and Behavior

4.2.1. Impact on Office Load

To examine how offices respond to the dependent expansion, I take into account the size of the expansion in their relevant market. However, offices may draw patients from outside of their county of operation, indicating that they may be located on the boundary of a county or that because of less dense population areas, they compete with offices that are further away in other counties. As a result, the relevant market boundaries for offices should not be determined by the geopolitical boundaries set by county definitions, and offices will instead respond to changes from the dependent expansion across the counties encapsulated by its market boundaries. I describe then in the following subsection how I define markets for each office and measure the office-specific shock from the dependent expansion implied by the market definition.
Office-Specific Market Definition and Measuring the Office-Specific Shock from the Dependent Expansion

A challenge in the data is that there is extremely limited information on the geographic location of offices and consumers, with counties being the finest level of geographic information available. For offices that are located on the boundaries of counties and thus effectively operate in multiple counties, this introduces measurement error into the size of the dependent expansion shock. Using the size of the shock (the eligible ratio) for the county of operation for the office is not sufficient - the office may be responsive also to the dependent expansion shock in neighboring counties. To capture this, I use a variation of the Elzinga-Hogarty approach to define the market specifically for each office using data I have on the Euclidean straight-line distance between each patient and the office seen by the patient, which was calculated by programmers at Delta Dental of Michigan prior to masking the locations of patients and providers.\(^3\)

The Elzinga-Hogarty approach allows for a variable radius specific to each facility and based on patient flow, where the convention is to base the radius for each facility (generally hospitals) on the 75th and 90th percentile distances for patients to the facility. Because results for using the 75th percentile radius are virtually identical to those using the 90th percentile radius, I use the 90th percentile radius for each office for the Elzinga-Hogarty approach. This indicates that 90 percent of patients seen in the office travel less than or equal to the radial distance. I also use an alternate approach, where the radius is fixed by the county of operation to take into account the distances generally traveled to offices within the county of operation, which differentiates between rural and urban areas. This does not capture variation in how far patients will choose to travel dependent on the quality of dental offices, whereas the traditional Elzinga-Hogarty approach will allow offices that are perceived by patients to be higher quality to have a larger radius. In general, the alternate approach is more conservative than Elzinga-Hogarty, which will allow markets to be larger.

\(^3\)Jones et al. (2010) demonstrates that the difference between Euclidean straight-line distances and driving distances is unlikely to influence the outcome of analyses.
To calculate the office-specific measure of the dependent expansion, I use the office-specific radius obtained either through Elzinga-Hogarty or the alternate approach with the data prior to the implementation of the dependent expansion to calculate the ratio of patients travelling within the market from each county. I then use the ratio of patients in each county surrounding the office as a weight to proxy the relative exposure to the dependent expansion in each county. The ratio of patients in each county is thus multiplied by the size of the dependent expansion (the eligible ratio) in the county, and then summed for a office-specific measure of the dependent expansion. The office-specific measure is thus calculated as follows:

\[
\text{Elig\ Ratio}_p = \sum_c (\text{Elig\ Ratio})_c \times \frac{\# \text{Patients Pre-Expansion Traveling } \leq r_p \text{ from county } c}{\# \text{ Patients Pre-Expansion Traveling } \leq r_p}
\]

where \(p\) indicates the office, \(c\) indicates the county, and \(r_p\) indicates the radius associated with the office \(p\). This assumes that 1) residents of each county are equally dispersed within the county, and 2) the newly enrolled individuals from the dependent expansion will have similar travel patterns as those who were enrolled prior to the expansion. The office-specific eligible ratio then is a measure that smooths the size of the dependent expansion across all the counties the office receives patients from prior to the expansion. The theoretical result is that this allows offices to be relatively more exposed to shocks in counties where they draw a larger proportion of patients prior to the expansion.

A potential weakness of Elzinga-Hogarty methods of defining markets is that it can "lead to large catchment areas that do not accurately reflect the level of a [facility’s] market power". In this case, there is no definitive direction of the bias from larger catchment areas - the office-specific eligible ratio may be higher or lower than the eligible ratio for the eligible ratio faced by the office given a smaller market definition. Other than defining the radius of the Elzinga-Hogarty approaches to be smaller, the finest market definition available given the data is defining markets to be counties. Hence, I compare the office-specific eligible
ratio to the eligible ratio for the office’s county of operation in Figure 9. In Panel (a), I find that consistent with how the office-specific (market) eligible ratio was defined, there is a clear linear relationship between the market eligible ratio and the county eligible ratio. Furthermore, in Panel (b), the distribution of the error terms from the regression of the market eligible ratio on the county of operation eligible ratio is normally distributed around zero, indicating that there is not a clear direction to the bias.

I also use this modified Elzinga-Hogarty approach to generate the weighted market characteristics that vary over time that each office responds to. I take the weighted average across counties that the office receives patients from for the following variables: the size of the population without any form of insurance (between ages 18-64), the unemployment rate, the number of individuals per office in an age group (taken as the population size in a county for an age group, divided by the number of general offices in the county), and the total population size. These weighted market characteristics will be used in the office-level analyses to control for changes over time that impact the market.

A noted shortfall of this approach is that though I can approximate the size of the market in terms of the number of people that may choose to go to a given office over other offices, I cannot know whether an office is within the bounds of another office’s markets. As a result, market fixed effects and the number of offices per market cannot be used as controls in the regression analyses, though the number of offices per county can be used as a control.

4.3. First Stage Regressions

Using the office-specific market shock from the dependent expansion, measured by the weighted average of the ratio of young adults in the population across the counties the office draws patients from, I implement a difference-in-differences regression with variable treatment intensity to describe the impact of a market expansion on the number of patients among offices. Because an increase in the ratio of young adults in the population will lead

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4The uninsurance rate among those under age 19 is also available, but because of collinearity with the uninsurance rate among those between ages 18 to 64, this was omitted from the regressions.
to a larger office-level shock for counties with larger overall populations relative to smaller populations, I restrict to offices located in markets with more than 250,000 people in the population, which captures 66.4% of the office sample.

There are multiple advantages to restricting the sample to offices located in larger markets. First, conditional on the eligible ratio, offices in larger markets are more likely to have larger responses to the eligible ratio. Second, this makes it more likely that offices within the sample that face larger eligible ratios operate more similarly to those facing smaller eligible ratios. This is especially important given that the set of observable office characteristics and market characteristics is limited in the data. In particular, offices that operate in smaller markets may face a different market structure (i.e. less competitive) than those that operate in larger markets, and this may impact how they respond to sudden increases in market demand and in office load. As a result, restricting to the set of offices that operate in larger markets may help to control for any time-varying changes that disproportionately affect offices in larger markets over those in smaller markets.

Along similar lines, I construct a second office-level sample to contain only general offices that provide root canal treatment. Based on anecdotes given by an endodontist, general dental practitioners who feel that they are able to provide root canal treatment may choose to provide more root canal treatments in-office rather than referring to an endodontist in periods of low demand. As a result, offices who are able to generate income through root canal treatments would be operating more similarly to other offices that also provide root canal treatment. Furthermore, anecdotes from dentists suggest that these may be offices that are more likely to engage in demand inducement, because in-house root canal treatments at a general dentist’s office result in measurably worse clinical outcomes relative to at an endodontist’s office. As a result, offices that are more likely to engage in demand inducement are more likely to respond to shocks that influence the financial incentives to induce demand.

To show that the sample restrictions may control for unobserved differences between offices
facing larger and smaller expansions, I look at various dimensions of the quantity and intensity provided among offices in high expansion markets relative to low expansion markets in 2010, the year preceding the implementation of the dependent expansion. An office is defined to be in a high expansion market if the office-specific eligible ratio exceeds the mean office-specific eligible ratio in the particular sample of interest. The variables examined in this table are the total number of patients under age 65 in each office, the total number of visits, the total number of tooth fillings (total and by intensity), the total number of root canals, and the total number of extractions in 2010. Many of the mean differences between offices in high and low expansion markets are statistically different in the full office sample, which is influenced by the large amount of heterogeneity in the size of the market of operation. Restricting to offices that operate in larger markets (above 250,000 in population) leads to offices that are very similar to each other on the all measures other than the number of extractions in a year among patients under age 65. Further restricting to offices that are likely to be higher-intensity offices (because they are general dental offices that carry out root canals instead of referring high severity cases out to dental specialists) does not lead to substantial changes between the offices in high and low expansion markets. This also serves to address concerns that the underlying treatment intensity or demand for procedures is different for offices that are facing larger versus smaller expansions, such that the instrument would be correlated with the underlying factors influencing treatment intensity.

To measure changes in how busy an office is over time (which I call office load), I use the number of patients under age 65 and the number of visits among these patients. The main proxy for office load of interest in this analysis is the number of patients, because the number of visits per patient is a choice variable for the dental provider (the dentist and the patient together determine how many visits to have in a year; hence, the number of visits per patient is not exogenously assigned). However, the shock to office load may be underestimated by examining only the number of patients under age 65 if, for instance, new patients enter dental offices with high levels of severity and require more visits.
I test for parallel trends for the difference-in-differences analysis by implementing the following regression specification:

$$
\log(\# \text{ Patients in Age Group})_{pct} = \beta_0 + \beta_{1t}1(\text{High Office-Specific Eligible Ratio})_p + \beta_2 X_{pt} + \psi_p + \eta_c + \gamma_t + \epsilon_{pct}
$$

where $p$ indicates the dental office, $c$ denotes the county of operation, and $t$ indicates the year. I use the log of the office-specific eligible ratio (which is time-invariant) to take into account that the distribution of the eligible ratios is skewed. I take the log of the number of patients per office-year to address the concern that though some offices may have a relatively large level increase in the number of patients, this may not be a substantive shock to the office depending on the baseline level of patients in the office. However, the standardized coefficients using a regression specification with levels for both the dependent and independent variables of interest results in quantitatively identical results to the log-log specification described here. I do not include the level-level regression results here to avoid duplication. Hence, percentage increases in the number of patients within the office are more directly of interest. The $\beta_{1t}$ are the coefficients of interest. The $\beta_{1t}$ coefficients map the average impact of the expansion across all offices relative to 2008 as the base year and is interpreted as the average percentage increase in the number of patients for an office from having a "high" office-specific eligible ratio, where "high" in this context is taken to be in the topmost quartile of the distribution of office-specific eligible ratios. The choice to use a binary variable in lieu of the continuous office-specific eligible ratio is stylistic - the results from the parallel trends test are robust to using the continuous variable or other cutoffs for the "high" definition - and mostly allows for a more elegant graphical presentation. Similarly to the county-level regression specification, I account for variation over time in market conditions by including variables in $X_{pt}$ (the index $p$ reflects that the markets are defined for each office) to avoid omitting time-variant factors that may be correlated with the change from the dependent expansion. These variables include the size of the
population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate, all taken as weighted averages across counties encapsulated in the market boundaries with weights specified in the modified Elzinga-Hogarty approach described earlier. In practice, using the modified Elzinga-Hogarty weighted means do not influence the results substantially relative to using the characteristics of the county of operation for each office. Additionally, the number of individuals per office in an age group is included as an additional county-level, time-varying regressor to account for changes in population sizes among specific age groups that may impact office take-up of patients of these ages. This variable also serves as a control for differences in utilization over time that is associated with dentist supply that may be correlated with the size and timing of the dependent expansion shock. I include also office fixed effects (which is possible because balance was imposed upon the office-level sample), county fixed effects, and year fixed effects.

In implementing these office-level regressions, I collapse the 15 to 19 and 20 to 24 year old age groups into a single 15 to 24 year old age group, primarily because individuals of these age groups comprise a relatively small proportion of dental offices. Likewise, I collapse the 25 to 29 and 30 to 34 year olds age groups into a single 25 to 34 year old age groups for the same reason. Historically, dental offices have had difficulty capturing individuals of these ages primarily because this group faces the highest cost barriers to care and dental insurance, and were not likely to have had an offer of employer-sponsored dental insurance, whether as an employee or as a dependent.

Figure 11 graphs the $\beta_{1t}$ coefficients for the parallel trends test specified above, for offices operating in high population markets (greater than 250,000 people under age 65 in the market population). The figure for the entire sample of offices is excluded here, due to strong similarities. As in the county-level analysis, there is no statistically significant percentage increase in the number of patients per office relative to 2008 baseline levels in 2009 and 2010 across all age groups, but there is a statistically significant percentage increase in the number of patients under age 65, between ages 15 and 24, and between ages 35 and 64 beginning in
2011, the first effective year of the dependent expansion. The youngest age group, made up of individuals between ages 0 and 14, see steady but statistically insignificant percentage increases in the number of patients per office for all years except for 2013. This may be attributable to the somewhat delayed implementation of the dependent expansion, which, as mentioned previously, was due to delays in employee awareness of the dependent expansion in employer-sponsored dental insurance plans.

To summarize the overall effect of the dependent expansion, I implement the following regression:

\[
\log(y_{pct}) = \beta_0 + \sum_{t=2011}^{2013} \beta_t \log(\text{Office-Specific Eligible Ratio}_p)1(\text{Post}) + \beta_2 X_{pt} + \psi_p + \eta_c + \gamma_t + \epsilon_{pct} \tag{4.1}
\]

where \(y_{pct}\) is the measure of office load for an office \(p\) in county \(c\) and year \(t\), which is measured using the number of patients per office and the number of visits per office. The main coefficients of interest are the \(\beta_t\) which are the average effect of the dependent expansion across offices in each year following implementation of the expansion (2011 through 2013). Time-varying market characteristics, given by \(X_{pt}\), and include the size of the population without any form of insurance (between ages 18 to 64, and under age 19), the unemployment rate, the number of individuals per office in an age group, and the total population size of the market in each year\(^5\). I implement this for all three office samples - all offices, offices in high population (more than 250,000 individuals under age 65 residing in the market) (called the ”250K” sample), and offices that are in high population markets that are able to carry out root canals (called ”Self-Referral” sample, because these offices have a choice to refer high-intensity specialist treatments to specialists or to themselves).

\(^5\)Recall that markets are defined for each office, so that market characteristics are a weighted average of the characteristics of counties that an office draws patients from.
To adjust for changes in the distribution of the office-specific eligible ratio across samples, which affects the scale of the estimated coefficients, I calculate the mean and standard deviation for the log of the office-specific eligible ratio in each sample and generate the standardized version of this variable by subtracting the sample mean from the original value and divide by the standard error in the sample. This yields a more straightforward coefficient interpretation.

The standardized coefficient estimates of interest in Table 16 describe the average percentage increase in office load from one standard deviation increase in the log of the office-specific eligible ratio. An increase in one standard deviation in the office-specific eligible ratio leads to an average 3.6% increase in the number of patients under age 65 for the 250K sample, and an average 3.3% for the self-referral sub-sample. Both coefficient estimates for each office-level sample are highly statistically significant at the 1% level. Though the scales are different, these coefficients are in range of the effects estimated at the county level in Table 11, where a one standard deviation in the county-level eligible ratio led to a 2.59% increase in the number of people enrolled in the county under age 65.

Table 17 uses the number of visits among patients under age 65 per practice as an alternate measure to detect increases in office load from the dependent expansion. Overall, an increase in one standard deviation in the office-specific eligible ratio leads to an average 3.92% increase in the number of visits under age 65 in the 250K sample, with a slightly more muted effect in the self-referral sample (consistent with the preceding analysis using the number of patients as the measure of office load) of 3.49%. As a result, using number of visits as the alternate measure of office load increases the estimated impact from the dependent expansion, though the coefficient estimates are in reasonably bounds of the coefficient estimates from Table 16 using the number of patients as the measure of office load.

Given that the top 5% of offices in the 250K sample are more than 2.64 standard deviations above the mean, column (1) of Table 16 suggests that offices at the 95th percentile on
average experience a 9.5% increase in the number of patients under age 65. This is well within the upper bounds of the estimates calculated with the county-level analyses, which suggested up to a 9.2% increase in the number of patients with one standard deviation increase in the county eligible ratio. Similarly, the 95th percentile of the distribution of offices in the Self-Referral sample is 2.72 standard deviations away from the mean, implying a 8.9% increase in the office load from the dependent expansion. As a result, the increase in office load from the dependent expansion is non-trivial and may be a large enough shock to alter provider incentives for demand inducement.

To show that the effect comes primarily from the age groups of interest, I carry out the same regression specification, but using as the dependent variables the number of patients in each age group per office-year. Table 18 contains the standardized coefficient estimates for the regression specification described in Equation 4.1, using the log of the number of patients in each age group as the dependent variables. I find primarily that there are highly statistically significant increases among patients who are directly targeted by the expansion (15 to 24 year olds), those who are young enough to be eligible (0 to 14 year olds) and patients who are old enough to be parents of dependents (ages 35 to 64). The estimated effect of a one standard deviation increase in the office-specific eligible ratio on the percentage increase in the number of patients is greatest among the 0 to 14 year olds with a 3.64% increase, followed by the 15 to 24 year olds with a 3.57% increase, and then the 35 to 64 year olds with a 3.51% increase. This is consistent with the prior county-level regressions combined with the average travel distances by age group, because though the greatest increases in coverage were among those directly targeted by the dependent expansion (15 to 24 year olds), this was also the age group with the furthest travel distances to dental providers primarily because of college or not living in the same residence with their parents (which cannot be directly measured or detected with this data). As a result, the increases in patients among ages 15 to 24 in offices would be muted relative to the increases in coverage in response to the dependent expansion, because those ages 15 to 24 would not be as likely as those in other age groups to visit providers within the same market. In contrast, there is
no statistically significant increase in the number of patients between ages 25 to 34, which is comprised of patients who are too old to be eligible for the dependent expansion, but primarily not old enough to have children that are directly eligible for the expansion. This is consistent with the earlier county-level results that found that the increases in enrollment from the dependent expansion among 35 to 64 year olds was driven by 35 to 64 year olds enrolled as parents, not by those who were not enrolled as parents.

Though the use of an industry-level predictor of the size of the dependent expansion (the eligible ratio) may ameliorate concerns about whether the increase in enrollment is shared across the dental insurance industry and not exclusive to Delta Dental, one may still be concerned that the influx of patients into offices as measured by the Delta Dental data does not actually represent a shock to the office, but represents instead existing patients in the office switching dental insurers or insurance statuses and newly appearing in the DDMI data, but are not new to the practice. This would be the case if Delta Dental carried out business-stealing, which would imply that the measured increases in enrollment described earlier were not true increases in dental market demand.

To fully neutralize the business-stealing argument, I introduce the use of a combination of procedures codes in dental claims data that helps to distinguish whether increases in enrollment in any year were due to business-stealing actions on the part of Delta Dental or represented real increases in dental market demand. Because Delta Dental has 93% of all dental providers in its main states of operation contained in its networks, the likelihood that an individual who is switching insurers is also switching providers is not very high. In addition, there are several specific procedure codes common across all dental claims datasets that are utilized only for patients who are new to the practice and/or have not been seen at the dentist in the past three years. These are the codes D0150 and D0180, which are respectively Comprehensive Oral Evaluation New or Established Patient and Comprehensive Periodontal Evaluation New or Established Patient. Discussions with both claims administrators at the University of Pennsylvania School of Dental Medicine and
with dentists suggest that there is little incentive to code established patients that have been seen continually in the practice using these dental procedure codes, because these codes require more services to establish a new dental history for the patient and if these services are found to be lacking, the dental provider opens himself up for litigation. As a result, if business-stealing is occurring within the data, and the majority of new enrollees in Delta Dental in a given year are switching coverage from other insurers or were uninsured and seeing the dentist previously, then an increase in enrollment should not lead to an increase in the number of new patients within practices or within counties. Conversely, if an increase in enrollment leads to an increase in the number of new patients, then the increase in enrollment can be interpreted as a true increase in market demand.

Because there is little financial incentive to use the new patient coding, the new patient codes are likely to be underused, making it more difficult to detect changes in the number of new patients in each year per office. To mitigate this issue, I calculate the minimum number of new patients coded in each office over the entire time period and remove from the sample offices in the bottom and top 5% of the office-level distribution of the minimum number of new patients. This serves to remove offices that rarely or never use the new patient coding (bottom 5%) and offices that often use the new patient coding. Either scenario suggests that these offices in the bottom and top 5% of the distribution either do not use the new patient coding as other offices or are operating differently from other patients (for instance, offices that tend to see many new patients in each year may have higher levels of turnover relative to other offices). Because offices are likely to underuse the new patient coding, even after removing offices that seldom or never use the new patient coding, I expect that the estimates of the effect of the dependent expansion on new patients will be biased towards zero.

The resulting increase in the number of new patients is examined in Table 19 by implementing equation 4.1 and replacing the dependent variable with the log of the number of new patients in each age group. The results are given in Table 19, which finds that the most
substantive increases in new patients comes from the target age group (ages 15 to 24) and the individuals between ages 35 and 64 who are parents of 18 to 26 year olds. In contrast, there are no statistically significant increases in the number of new patients among other age groups, among parents of 0 to 17 year olds, and among non-parents. This increases confidence that the proxy for the dependent expansion is capturing true increases in office load, and among the groups of interest. The lack of a statistically significant increase in the number of new patients between ages 0 to 14 is in contrast to the statistically significant increase in the number of patients found earlier in Table 18. However, because there is little financial incentive to use the new patient coding, it is likely that using this measure of increases in patient load captures only the most dramatic increases in patient load. Hence, the most detectable changes in the number of new patients per office in response to the dependent expansion are among the age group targeted by the expansion and their parents.

As a result, the increase in office load is substantive with offices at the 95th percentile of the distribution (among the 250K sample) experiencing an average predicted increase of 9.5% in office load from the dependent expansion. Furthermore, the increases come from the age groups of interest - those young enough to be eligible for the expansion and those old enough to be parents of eligible dependents - with the most dramatic increases coming from the 15-24 year olds and the parents of the directly eligible (ages 18 to 26). These results align with the prior county-level analyses and verify that the increase in patient load is from the dependent expansion and not any other concurrent change in the market during the post-implementation period of the dependent expansion.

4.4. Impact on Treatment Decisions from An Increase in Office Load

4.4.1. Measurement of Treatment Intensity/Quantity

Providers can primarily alter the intensity of care for patients through two pathways - frequency of visits and treatments and intensity of treatment. To measure changes in frequency of care, I examine the number of visits and the number of routine visits per
continuously insured patient on average within an office, where I define routine visits to be visits that are comprised entirely of routine procedures typically covered at 100% (within the yearly frequencies determined by the insurer.

To measure changes in overall treatment intensity by providers over continuously insured patients, I measure the average number of procedures by procedure categories, where the different procedure categories indicate lower and higher intensities of treatment. For instance, I separate cavities into cavities with one-, two-, three-, and four or more surfaces, where one-surface cavities are the least intrusive and least intensive cavity filling procedure and four-surface cavities and up are the highest intensity (without moving towards root canals and other more involved procedures typically requiring dental specialists). I also broadly separate routine from non-routine procedures, where routine procedures are those typically covered generously by dental insurance plans, such as routine examinations, cleanings, and X-rays. The average quantity within each procedure category indicate the quantity of each type of procedure across the relevant group of patients. I construct average quantities for continuously insured patients and continuously insured and continuously seen (at least once a year) patients. Increases in the average number of high-severity procedures (such as fillings with three or more surfaces, or root canals) per continuously insured patient indicate increases in treatment intensity by providers, since the continuously insured patient cohort is constant throughout the time period for each office and is not changing in its underlying severity nor facing changes in dental coverage that would alter patient demand for services. Restricting to analyzing changes in average treatment intensity and frequency among the continuously insured and continuously seen patient cohort controls even more strictly for the underlying severity and composition of the patient group, because this group receives continuous management of their underlying oral health condition which likely is closely correlated to better oral hygiene habits and decreased likelihood of sudden onset of caries or other adverse oral health conditions.

I also construct average patient and insurer payment amounts per year, averaged across all
patients within each subgroup in each practice to analyse how changes in quantities and intensities alter payment amounts by both patients and insurers.

4.5. Endogeneity Concerns and OLS Results

The ultimate goal of this research is to analyze how substantial changes in office load (measured primarily in the number of patients per office) impact treatment behavior, by using a change in office load that is plausibly exogenous. As a result, this research is most concerned with whether providers’ treatment decisions respond to the size of a shock from the number of new patients added into each office. The plausible exogeneity has been established in the prior sections, but is key particularly to analyzing the impact on treatment decisions, primarily because there is an endogeneity problem here.

There are two sources of concern here. The first is an endogeneity concern - there may be omitted variables or unobserved variables that mediate the relationship between the number of patients an office attracts and its average intensity or quantity of dental treatments. For instance, if one were to regress directly the average treatment quantity of an office across its patients on the number of patients attracted by an office, there may very well be a positive correlation that could not be construed as causation. This is because omitted variables, such as quality, may be influencing this relationship. A plausible story is that patients may perceive offices that implement more treatments or higher intensity treatments to be higher quality, and thus flock to these offices, leading offices that are higher intensity/quantity to have more patients. Hence, a priori, there should be a positive correlation between number of patients in offices and treatment quantity if the following naive OLS regression is estimated:

\[
\log(y_{pct}) = \kappa_0 + \kappa_1 \log(\# \text{ Patients } < 65)_{pct} + \kappa_2 X_{ct} + \psi_p + \eta_c + \gamma_t + \epsilon_{pct}
\]
where \( p \) indicates the office, \( c \) the county, and \( t \) the year. \( y_{pct} \) captures the average treatment quantity of an office across its patients over time. I take the log of the dependent variables (the average quantity of treatment per patient) because both baseline levels and level changes in the average treatment quantity per patient may also be small. As a result, percentages make it easier to determine how impactful the change in the treatment is relative to baseline levels. However, using levels for the dependent variables and the independent variables of interest result in standardized coefficients that are quantitatively identical to the results using the log-log specification described here.

Tables 20 through 22 contain the results of the naive OLS regression for the 250K office-level sample and a variety of measures of treatment intensity, where I directly regress the log of the average treatment intensity of treatments among all patients on the log of the number of patients under age 65. The estimated coefficients support the underlying story about quality driving a positive relationship between quantity of treatment and the number of patients seen within an office. Regardless of intensity of treatment, whether one-surface or three-surface cavities, the OLS regressions find that there is a positive correlation between the number of patients at an office and the quantity of treatments. For instance in Table 20, a 100% increase in the number of patients under age 65 is correlated with a 2.79% increase in the average number of cavities per patient and a 1.64% increase in the average number of 1-surface fillings per patient. Furthermore in Table 21, a 100% increase in the number of patients under age 65 is correlated with a 3.98% increase in the average number of routine visits per patient and a 8.74% increase in the average number of visits per patient.

An interesting pattern to note is that the positive correlation between office load and the number of cavity procedures of each type diminishes in magnitude as the severity of the procedure increases. A 100% increase in the number of patients under age 65 is correlated with a 1.64% increase in the average number of surface 1 fillings per patient, a 0.87% increase in the average number of surface 2 fillings per patient, a statistically insignificant but still positive 0.59% in the average number of surface 3 fillings per patient, and a statistically
insignificant but still positive 0.28% in the average number of surface 4 fillings per patient. Moving up in intensity for cavity procedures leads to the coefficient of interest becoming a degree of magnitude smaller, but remaining still positive. There is also a statistically insignificant and positive 0.009% increase in the average number of root canals per patient in response to a 100% increase in the number of patients, where the coefficient is smaller than the coefficient on four-surface cavities. This may suggest that though perceived quality may be positively correlated with the number of procedures provided, perceived quality also diminishes as the severity of procedures increases. The positive coefficient for root canals provides some suggestive evidence that demand inducement may be carried out by general dental practitioners, simply for the fact that the clinical outcomes of root canals done by general dental practitioners are far worse than those done by endodontists, who are specially trained to carry out endodontic procedures.\(^6\)

The increases in treatment among larger practices relative to smaller practices primarily manifest in higher payments for the insurer, where a 100% increase in the number of patients is correlated with a 31.7% increase in the average yearly insurer payment amount to the provider. This, along with the statistically insignificant effect on yearly patient out-of-pocket amounts (Column 4 of Table 21), suggest that larger offices primarily can increase provision of treatments for patients primarily by increasing quantity and intensity among treatments that are covered generously by the insurer, which would yield little in out-of-pocket cost increases for patients.

The positive correlation between the number of patients in the practice and the number of routine procedures is most prominently seen for oral evaluations, cleanings, and diagnostic imaging, which were previously discussed to be among the most profitable services for general dental practitioners to offer. For instance, a 100% increase in the number of patients under age 65 is correlated with a 6.18% increase in the average number of yearly cleanings per patient and a 7% increase in the average number of diagnostic imaging procedures

\(^6\)Discussed previously in Chapter 2
per patient, both with a high level of statistical significance in Table 22. There is also a statistically significant positive correlation between the office load and the average number of fluoride treatments and sealant treatments provided per patient, but the magnitudes are smaller than for the correlations for the most profitable treatments.

Additional notable exceptions to the statistically significant positive correlations between frequency of treatment and office load are extractions. Extractions are typically the last choice of procedure (unless followed up by dentures or implants) for dentists for both clinical and financial reasons. Extractions remove the original tooth structure, which is undesirable from a clinical standpoint, and are reimbursed very little. Anecdotally, dentists say that extractions are typically used only when the patient cannot afford other treatments or is otherwise income-constrained. As a result, there is a negative, statistically insignificant correlation between the average number of extractions per patient and the number of patients per dental practice.

Hence, using the OLS regressions in Tables 20 through 22 would lead one to conclude that an insurance expansion that increases the number of patients in practices would lead to increases in the frequency of all services for all patients. This is clearly erroneous, given that additional increases in routine procedures alone would lead to increases in out-of-pocket cost for patients due to limitations on the frequency of routine procedures under dental insurance plans. Furthermore, this would imply that offices could increase frequency of all procedures without facing adverse consequences from patients and insurers.

A secondary concern is that even if we were to control for omitted variables across offices, offices may strategically increase the number of patients they have over time, by increasing outreach to patients or advertising. As a result, offices that are observed to have increases over time may very well be expecting the increases by adjusting their office capacity (for instance, by hiring more dental hygienists or increasing the physical size of the office and the number of chairs in the office) in anticipation of the increased patient numbers. Hence, the increase in the number of patients in the practice is not a shock to the office, and
as a result, would bias the relationship between patient numbers and treatment intensity towards zero. However, the use of the dependent expansion ameliorates concerns about this issue, primarily because the dependent expansion within dental insurance was unexpected and led to sizable increases in office load as discussed in the previous section.

4.6. Instrumental Variables Results for All Offices

To analyze the impact of the increase in the number of patients per office from the dependent expansion on treatment decisions, I implement an instrumental variables strategy, using the earlier difference-in-differences specification as a first stage, estimated via two-stage-least-squares (2SLS) with office and county fixed effects. The instruments are the interactions between the post-implementation dummy for the expansion (equal to one for 2011 and the years following) and the size of the office-level shock from the expansion (measured via the log of the office-specific eligible ratio). The first stages for each sample are contained in Table 16. These instruments isolate the increases in office load, measured in the number of patients under age 65, that come solely from each office being exposed to the market-level shock from the dependent expansion. As a result, this removes any variation in office load that comes from unobserved quality across offices, which was the endogeneity concern described earlier.

To control for changes in underlying severity of the patient cohort and to ameliorate concerns about changes in patient preferences for treatment, due to changes in insurance coverage, I examine the impact of the exogenous increase in office load on the average quantity of services across continuously insured patients in an office for each procedure and visit type, $z_{pct}$. This implements directly the hypothesis test described in the Theory section. The

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*I choose to examine average treatment intensity across a fixed cohort of patients instead of implementing a patient-office-year level regression primarily because I am limited in the amount of patient characteristics that can be introduced into the regressions and fixed effects for each continuously insured patient threatens to difference away much of the variation, especially because continuously insured patients would not be likely to have significant changes over time in their underlying severity or demand for procedures.*
second stage is then the following:

\[ \log(z_{pct}) = \kappa_0 + \kappa_1\log(\#~\text{Patients} < 65)_{pct} + \kappa_2X_{ct} + \psi_p + \eta_c + \gamma_t + \epsilon_{pct} \]

where \( p \) indicates the office, \( c \) the county, and \( t \) the year. Office, county, and year fixed effects are included, as well as time-varying market characteristics. Standard errors are clustered at the county level to adjust for correlations among offices within the same county, and observations are weighted by the estimated size of the market population in 2011 constructed using the modified Elzinga-Hogarty method. 8

The IV results for patients who are continuously insured between at least 2008 to 2013 for the 250K sample of offices are contained in Tables 24 through 25, which explicitly test Hypotheses 1 and 2. Notably the F-statistic for the first stage, which takes on a value of 18.77, is above the Stock-Yogo weak identification test critical value for a 10% maximal IV size, 16.38 - hence, weak instruments are not likely to be a problem here. There are on average 131.7 continuously insured patients per office contained in the sample, which allows one to be reasonably satisfied that any changes in treatment behavior over time across the office on average for continuously insured patients are being measured with some degree of accuracy and is not driven by outliers. In Table 23, Panel B, I find that there there are no increases in the average frequency of routine visits for continuously insured patients from a percentage increase in the number of patients from the dependent expansion. This is an intuitive result, because among insurance plans, two routine visits per year per patient is the recommended norm (and implicitly enforced through coverage rules on the frequency of routine procedures), and there is an average of 1.974 routine visits among continuously insured patients, giving dental providers little room to increase the average number of routine visits. There are also no statistically significant increases in the number of visits, yearly plan costs, and yearly patient out-of-pocket costs in response to the increase in the

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8 Ideally, market-level fixed effects and clustering would be preferred over county fixed effects and county-level clustering, but this is a limitation of the data.
number of patients from the dependent expansion.

However, the statistically insignificant effect on the number of routine visits does not imply that there are no increases in routine procedures that are fully covered by the insurer at 100% within the routine visits that occur, nor that there are no increases in routine procedures in visits that are a mix of routine and non-routine procedures. Rather, there is a statistically significant increase in the average number of hygiene instructions given to continuously insured patients from the increase in the number of patients from the dependent expansion. Taken together with the statistically significant decrease in the average number of surface 3 and surface 4 cavities per continuously insured patient and increases in the average number of low-severity surface 1 cavities (statistically significant for surface 1 cavities and statistically insignificant for surface 2 cavities) in Table 25, this suggests that there is mild substitution away from higher intensity cavity procedures towards less intensive cavity procedures and more routine services that can be carried out by dental hygienists and are usually reimbursed for at 100%. This lends support for the hypotheses outlined in the theory section, primarily that offices that experience a larger increase in the number of newly insured patients in their practices will lead to a decrease in treatment intensity for the continuously insured. 9

I carry out the same analysis for the Self-Referral sample to test whether the results hold for a subsample of offices that are plausibly more similar and more likely to carry out demand inducement in Tables 26 through 28. The direction and statistical significance of coefficients largely align with those from the 250K sample. The most significant difference is

9The reader may be concerned that I am testing multiple outcomes per hypothesis here, which increases the likelihood of finding an effect from any one outcome variable. An easy way to adjust for this is to use the Bonferroni correction, which adjusts the critical value with which to judge the statistical significance of a result. Given that the cutoff for statistical significance is 10%, and there are less than ten treatments per grouping (among high intensity treatment vs. routine treatments), coefficients that are significant at the 1% level pass the Bonferroni correction for multiple hypothesis testing, which uses the critical value of $\alpha/n$. Because the Bonferroni adjustment assumes that outcomes are uncorrelated, it tends to be too conservative when outcomes are correlated. All results that are statistically significant in Table 24 through Table 25 remain statistically significant under the Bonferroni adjusted critical value except for the increase in the average number of surface 1 cavities per continuously insured patient. As a result, the interpretation of the results hold up even under the conservative Bonferroni adjustment.
that the impact of the increase in patient load from the dependent expansion on the number of diagnostic imaging procedures has increased in magnitude relative to the 250K sample (the coefficient has gone from a 15.8% increase in response to a 100% increase in office size from the expansion in the 250K sample to a statistically significant 21% increase in the Self-Referral sample) and become statistically significant at the 5% level. Additionally, the magnitudes for the decrease in the average number of high intensity cavity procedures (surface 3 and 4 fillings) per continuous patient are larger, and with larger numbers of procedures in each category at baseline (an average 0.119 surface 3 fillings per continuously insured patient across offices, and an average 0.0678 surface 4 fillings per continuously insured patient across offices in the High Referral sample). Hence, the group of offices that are most likely to carry out demand inducement were more responsive to the decreased incentive to induce demand, though as in the 250K sample, this led to no statistically significant changes in the average number of visits, routine visits, and yearly costs (insurer and out-of-pocket costs).^{10}

To be more stringent about controlling for changes in underlying severity in the composition of patients included for each office, I restrict the patient population to those who are continuously insured and have at least one visit for every year in the analysis (2008-2013). Because these are individuals who are seeing the dentist continually, this may imply that their underlying oral health condition is stable or an increased concern or awareness for their oral health. Results are contained in Tables 29 through 31. As expected, because the group of continuously seen and insured patients are less likely to face sudden changes in their oral health, there is no statistically significant effect in the average number of surface 4 cavities per continuously insured and continuously seen patients. However, there is a statistically significant decline in the average total number of cavities per patient which seems to come primarily from a decline in the average number of surface 2 and surface

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^{10}Using the Bonferroni correction, the increase in diagnostic imaging is not statistically significant. As a result, the interpretation of the results for the Self-Referral sample are on a whole identical to those for the 250K sample, though the estimated coefficients have increased in the Self-Referral sample, indicating a stronger response to the increase in the number of patients from the dependent expansion.
3 cavities per continuously insured and continuously seen patient, which may be because there is still potential room for dentists to overdiagnose small cavities even among highly adherent patients. However, there is a statistically significant increase in the average number of diagnostic imaging procedures and in the average number of hygiene instructions per patient in this group across offices, with magnitudes that are comparable to those from the preceding analyses using the continuously insured. This implies that the changes in treatment behavior faced by the continuously insured were not isolated only to the continuously insured, but were shared across the majority of patients.

To evaluate whether these changes in treatment behavior are reflected over entire offices, I examine the average treatment intensity and frequency for all patients seen within offices in the high population sample. Though there are compositional changes within offices, the direction of coefficients are in line with the preceding analyses with statistically significant decreases in the average number of surface 4 fillings per patient in response to the increase in patient load from the dependent expansion. There is also a statistically significant increase in the average number of diagnostic imaging procedures per patient with a magnitude comparable to all the prior analyses. As a result, this suggests that the shift away from intensive restorative procedures towards routine procedures was not isolated to continuously insured patients and to continuous patients, but took place across the entire practice. This is consistent with how providers are postulated to make practice pattern decisions - optimization takes place at the practice level, not at the individual level.

4.7. Welfare Implications

Overall, I find that the average number of non-routine procedures declines among the continuously insured patients, with the number of higher intensity cavity fillings carried out per person experiencing the largest declines. I also find that new patients experience a decline in the average number of intensive treatments in response to the expansion, suggesting that the overall changes in treatment behavior took effect across both continuously insured and new patients. Restricting the analysis to offices that were highly exposed to market-level
shocks suggests that not only did non-routine, high-intensity procedures decline, but that there was substitution towards routine procedures. Overall, the pattern of results consistently point towards a decrease in intensive cavity procedures and substitution towards less intensive, routine procedures, which is consistent with the earlier model of provider behavior with demand inducement.

However, is a decline in intensive cavity procedures unambiguously welfare-improving for patients? Given the clinical background discussed in Chapter 2, the decline in intensive cavity procedures is almost certainly welfare-improving provided that cavities were not left to increase in severity to be filled in later. However, if this were true, this would likely have been coupled with a persistent decline in the average total number of cavity fillings, and only Table 26 found a statistically insignificant negative coefficient - all other samples reported a statistically insignificant positive coefficient. Furthermore, this would imply large implicit costs from demand inducement, if this was a common form of demand inducement - actively delaying a cavity procedure for much later in order to reap higher costs may lead to 1) the patient becoming symptomatic and perceiving the quality of dental care provided to be low as a result, 2) higher risk of being detected by the insurer if cavities are persistently 3 surface fillings or greater, and 3) ethical costs to the provider from not providing care when necessitated. The decline in intensive cavity procedures, however, is not likely to have had a large impact on patient welfare, given the magnitude of the estimated coefficients.

What is more concerning is the increase in routine procedures that stemmed most from the increase in diagnostic imaging, and less from increases in cleanings. While the shift from restorative procedures to routine procedures suggested a decrease in inducement for higher intensity cavity procedures, this also suggests that the shift was towards low-intensity procedures reimbursed generously by insurers with little positive benefit to the patient in terms of prevention of cavities. I discuss this issue in further depth in Chapter 5.

Why would dentists not provide the low-intensity procedures prior to a shock to office load? There are several possibilities. First, there may be diminishing or negative returns from
providing too many treatments per patient. This is an argument based on Dranove (1988), where patients are able to infer that providers exceeding a treatment quantity or intensity threshold are engaging in inducement behavior and punish them as a result. There may also be increasing probabilities of being detected by the insurer by providing too many treatments per patient. Second, if patients do indeed perceive quality of a dentist’s office to be correlated with the number of procedures in lieu of providing more capacity-intensive and higher intensity treatments, providers may use an increase in diagnostic procedures in order to justify the decrease in the number of restorative procedures. Future work developing quality measures for dental practices may be useful in testing these mechanisms empirically.

4.8. Conclusion

To summarize, I use a novel dental claims dataset from Delta Dental of Michigan to examine the effect of an exogenous increase in market demand, coming from a dental insurance expansion effective starting in 2011, on provider treatment behavior in dentistry. Because dental offices tend to practice under-capacity and readily take on new patients, the dental market is an area where aggregate market shocks will more directly impact office loads and office-level outcomes. I detect that a one standard deviation increase in the potential size of the insurance expansion, proxied by the fraction of the population in each county that is directly eligible for the dependent coverage expansion, leads to a 2.82% increase in the coverage rate among those under age 65 on average across Michigan counties. This translates to a potential 9.2% increase in the number of patient under age 65 for the average office in Michigan. Furthermore, though the increase in coverage rates is most dramatic for the age groups directly eligible for the dependent expansion, there is also a substantial increase in coverage rates among the parents of those eligible for dependent coverage. The increase in enrollment from adults with dependents accounts for 50.3% of the increase in enrollment on average across counties. The spillovers in enrollment, as a result, are an important factor in how heavily offices are impacted potentially by the dependent expansion, especially given
the general difficulty of dental offices in capturing individuals between ages 21 to 34, an age group that faces the most significant cost barriers to care relative to all other age groups (Nasseh and Vujicic, 2015).

I then move to the office-year-level analysis and examine how offices respond to the dependent expansion in their market by using dosage difference-in-difference analysis. By constructing markets using a variation of the Elzinga-Hogarty approach and the data available on the Euclidean straight-line distances between each patient and the office seen by the patient, I construct the potential size of the dependent expansion at the office-level, which is a weighted average of the county-level shocks across all counties (within an office-specific radius). As in the county-level analyses, I find that increases in the number of patients per office from the dependent coverage expansion are concentrated first among the age groups directly impacted by the expansion, and then among the age group of individuals old enough to have eligible dependents. Furthermore, there is no detectable percentage change in the number of patients in the control group, made up of individuals too old to be eligible directly for the expansion and too young to have dependents impacted directly by the dependent coverage expansion. As a result, a one standard deviation increase in the potential size of the dependent expansion, as measured using the office-specific eligible ratio, yields a 3.6% increase in the number of patients under age 65 in the post-implementation period, relative to baseline levels in 2008. This implies that some offices could experience as large as an 9.5% increase in the number of patients in the dental office from the dependent expansion relative to 2008 levels, which is well within the bounds of the estimates of the increase in the number of patients per office from the county-level analysis. Furthermore, the increase in office load from the dependent expansion is non-trivial and may be a large enough shock to alter provider incentives for demand inducement.

The dosage difference-in-difference regression is then used as the first stage in an instrumental variables analysis, which seeks to remove the influence of any omitted or unobserved variables impacting both the number of patients attracted by an office and its average inten-
sity or frequency of dental treatments. Using the increase in office load from the dependent expansion, I find that the sudden shock in office load leads to a statistically significant decrease in the average number of intensive cavity procedures across continuously insured patients and a statistically significant and sizable increase in the average number of diagnostic imaging procedures per continuously insured patient, and modest increases in the average number of hygiene instruction per continuously insured patients. Because I include only patients who have been continuously insured throughout the time period, the increase in intensive cavity procedures is not from a sudden change in insurance coverage, thus removing any moral hazard effect or changes in underlying demand. The result taken together suggest that a sudden increase in an office’s workload leads to substitution away from intensive cavity procedures towards routine procedures. This is consistent with the predictions of models of demand inducement and provider behavior.

4.9. Tables and Figures
Figure 4: County-Level Distribution of Eligible Ratio in 2011

(a) County-Level Distribution of Eligible Ratio in 2011

(b) County-Level Standardized Normal Distribution of Eligible Ratio in 2011
Figure 5: Testing for a Break in Trend in Coverage Rates

Impact on County-Level Coverage Rates (Percentage Changes)

Notes: In this figure, I implement the parallel trends test to examine whether there are common trends between counties with larger and smaller eligible ratios in the pre-implementation period (2009 and 2010) relative to 2008. Each dot represents the coefficient estimate for the given year, where the mapped coefficients are the interactions between the county-specific eligible ratio and the year fixed effects. 2008 is used as the excluded base year. The coefficients used in these graphs are the standardized coefficients for ease of interpretation. Additional control variables included in these regressions are such as the log of the size of the population without any form of insurance (between ages 18-64, and under age 19), the unemployment rate, and the number of dental offices per county. The 90% confidence intervals are given by the bars around each coefficient point estimate. Standard errors are clustered at the county-level, and observations are weighted by the size of the under 65 population in each county.
Table 8: Unweighted Least Squares Regression of County Coverage Rates by Age Group on Young Adult Ratio (Log-Log)

<table>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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<td>0.0977</td>
<td>0.112*</td>
<td>0.105*</td>
<td>0.0642</td>
<td>0.0239</td>
<td>0.0851**</td>
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<td></td>
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<td>(0.0587)</td>
<td>(0.0581)</td>
<td>(0.0672)</td>
<td>(0.0677)</td>
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<td>-2.483***</td>
<td>-1.861*</td>
<td>0.389</td>
<td>-3.092**</td>
<td>-2.325*</td>
<td>-1.560*</td>
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<td>X</td>
<td>X</td>
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<tr>
<td>Year FE</td>
<td>X</td>
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<td>X</td>
<td>X</td>
<td>X</td>
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<td>X</td>
</tr>
<tr>
<td>Level Pre-Policy Mean</td>
<td>0.244</td>
<td>0.190</td>
<td>0.204</td>
<td>0.199</td>
<td>0.146</td>
<td>0.175</td>
<td>0.269</td>
</tr>
<tr>
<td>Enrollment Share Mean</td>
<td>1</td>
<td>0.170</td>
<td>0.0695</td>
<td>0.0628</td>
<td>0.0458</td>
<td>0.0491</td>
<td>0.512</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level  
*** p<0.01, ** p<0.05, * p<0.1

Note: This regression estimates the effect on the coverage rate of each age group (calculated to be the number of individuals enrolled in Delta Dental plans in the county in the age group, divided by the total number of people in the age group in the county) from being in a county with a larger proportion of young adults in the population (calculated as the number of young adults between ages 20 and 24 in the county divided by the total county population). Observations are at the county-year level. I use a log-log specification to take into account that the distribution for the young adult ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Notes: These figures maps the distribution of travel distances from the individual’s residence to the dental provider across individuals residing in Michigan and enrolled in Delta Dental of Michigan plans between 2007 and 2013 for each age group. Outliers with travel distances exceeding 50 miles are dropped.
<table>
<thead>
<tr>
<th>Dep Var: Log(Enrollment in Age Group)</th>
<th>(1) Under 65</th>
<th>(2) 0-14</th>
<th>(3) 15-19</th>
<th>(4) 20-24</th>
<th>(5) 25-29</th>
<th>(6) 30-34</th>
<th>(7) 35-64</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(County Eligible Ratio)*1(Post)</td>
<td>0.0828</td>
<td>0.130*</td>
<td>0.120**</td>
<td>0.0991*</td>
<td>0.0723</td>
<td>0.0157</td>
<td>0.0800**</td>
</tr>
<tr>
<td></td>
<td>(0.0497)</td>
<td>(0.0693)</td>
<td>(0.0536)</td>
<td>(0.0563)</td>
<td>(0.0647)</td>
<td>(0.0654)</td>
<td>(0.0380)</td>
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<td>2.980</td>
<td>1.914</td>
<td>6.561***</td>
<td>-1.721</td>
<td>-5.926***</td>
<td>-3.142</td>
</tr>
<tr>
<td></td>
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<td>(3.644)</td>
<td>(2.911)</td>
<td>(1.857)</td>
<td>(2.513)</td>
<td>(2.207)</td>
<td>(5.597)</td>
</tr>
<tr>
<td>Observations</td>
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<td>474</td>
<td>474</td>
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<td>474</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.275</td>
<td>0.228</td>
<td>0.248</td>
<td>0.415</td>
<td>0.394</td>
<td>0.237</td>
<td>0.303</td>
</tr>
<tr>
<td>Number of Counties</td>
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<td>79</td>
<td>79</td>
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<td>County FE</td>
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<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Level Pre-Policy Mean</td>
<td>138729</td>
<td>23879</td>
<td>9967</td>
<td>8148</td>
<td>5800</td>
<td>6808</td>
<td>72038</td>
</tr>
<tr>
<td>Enrollment Share Mean</td>
<td>0.170</td>
<td>0.0695</td>
<td>0.0628</td>
<td>0.0458</td>
<td>0.0491</td>
<td>0.512</td>
<td></td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Note: This regression estimates the effect on the number of individuals enrolled in Delta Dental for each age group from being in a county with a larger proportion of young adults in the population (calculated as the number of young adults between ages 20 and 24 in the county divided by the total county population). Observations are at the county-year level. I use a log-log specification to take into account that the distribution for the young adult ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Table 10: Standardized Coefficients for Table 8

<table>
<thead>
<tr>
<th>Dep Var: Log(Coverage Rate in Age Group)</th>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(County Eligible Ratio)*1(Post)</td>
<td>0.0282*</td>
<td>0.0306</td>
<td>0.0350*</td>
<td>0.0330*</td>
<td>0.0201</td>
<td>0.00749</td>
<td>0.0267**</td>
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<tr>
<td></td>
<td>(0.0142)</td>
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<td>(0.0184)</td>
<td>(0.0182)</td>
<td>(0.0211)</td>
<td>(0.0212)</td>
<td>(0.0110)</td>
</tr>
<tr>
<td>Constant</td>
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<td>-2.483***</td>
<td>-1.861*</td>
<td>0.389</td>
<td>-3.092**</td>
<td>-2.325*</td>
<td>-1.560*</td>
</tr>
<tr>
<td></td>
<td>(0.802)</td>
<td>(0.932)</td>
<td>(1.029)</td>
<td>(0.965)</td>
<td>(1.363)</td>
<td>(1.239)</td>
<td>(0.816)</td>
</tr>
<tr>
<td>Observations</td>
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<td>474</td>
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</tr>
<tr>
<td>R-squared</td>
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<td>0.168</td>
<td>0.171</td>
<td>0.234</td>
<td>0.413</td>
<td>0.096</td>
<td>0.274</td>
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<tr>
<td>County FE</td>
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<td>X</td>
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</tr>
<tr>
<td>Year FE</td>
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<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Level Pre-Policy Mean</td>
<td>0.244</td>
<td>0.190</td>
<td>0.204</td>
<td>0.199</td>
<td>0.146</td>
<td>0.175</td>
<td>0.269</td>
</tr>
<tr>
<td>Enrollment Share Mean</td>
<td>1</td>
<td>0.170</td>
<td>0.0695</td>
<td>0.0628</td>
<td>0.0458</td>
<td>0.0491</td>
<td>0.512</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Note: This regression estimates the effect on the Delta Dental coverage rate for each age group from being in a county with a larger proportion of young adults in the population (calculated as the number of young adults between ages 20 and 24 in the county divided by the total county population). Observations are at the county-year level. I use a log-log specification to take into account that the distribution for the young adult ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Table 11: Standardized Coefficients for Table 9

<table>
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<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
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<tr>
<td>Under 65</td>
<td>0.0259</td>
<td>0.0408*</td>
<td>0.0376**</td>
<td>0.0310*</td>
<td>0.0227</td>
<td>0.00493</td>
<td>0.0251**</td>
</tr>
<tr>
<td>0-14</td>
<td>(0.0156)</td>
<td>(0.0217)</td>
<td>(0.0168)</td>
<td>(0.0176)</td>
<td>(0.0203)</td>
<td>(0.0205)</td>
<td>(0.0119)</td>
</tr>
<tr>
<td>20-24</td>
<td>(6.716)</td>
<td>(3.644)</td>
<td>(2.911)</td>
<td>(1.857)</td>
<td>(2.513)</td>
<td>(2.207)</td>
<td>(5.597)</td>
</tr>
<tr>
<td>25-29</td>
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<td>474</td>
<td>474</td>
<td>474</td>
<td>474</td>
</tr>
<tr>
<td>30-34</td>
<td>0.275</td>
<td>0.228</td>
<td>0.248</td>
<td>0.415</td>
<td>0.394</td>
<td>0.237</td>
<td>0.303</td>
</tr>
<tr>
<td>35-64</td>
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<td>X</td>
<td>X</td>
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<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
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<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Level Pre-Policy Mean</td>
<td>138729</td>
<td>23879</td>
<td>9967</td>
<td>8148</td>
<td>5800</td>
<td>6808</td>
<td>72038</td>
</tr>
<tr>
<td>Enrollment Share Mean</td>
<td>1</td>
<td>0.170</td>
<td>0.0695</td>
<td>0.0628</td>
<td>0.0458</td>
<td>0.0491</td>
<td>0.512</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Note: This regression estimates the effect on the Delta Dental coverage rate for each age group from being in a county with a larger proportion of young adults in the population (calculated as the number of young adults between ages 20 and 24 in the county divided by the total county population). Observations are at the county-year level. I use a log-log specification to take into account that the distribution for the young adult ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Table 12: Unweighted Least Squares Regression of Number of Enrolled Between Ages 35-64 by Parental Status on Eligible Ratio (Log-Log)

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
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</tr>
</thead>
<tbody>
<tr>
<td>Log(# Enrolled Between Ages 35-64)</td>
<td>0-26</td>
<td>0-17</td>
<td>18-26</td>
<td>Non-Parents</td>
</tr>
<tr>
<td>Log(Eligible Ratio)*1(Post)</td>
<td>0.0905**</td>
<td>0.137***</td>
<td>0.0307</td>
<td>0.0676</td>
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<tr>
<td></td>
<td>(0.0361)</td>
<td>(0.0443)</td>
<td>(0.0346)</td>
<td>(0.0443)</td>
</tr>
<tr>
<td>Constant</td>
<td>-2.964</td>
<td>2.375</td>
<td>-7.294</td>
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</tr>
<tr>
<td></td>
<td>(7.035)</td>
<td>(7.323)</td>
<td>(7.810)</td>
<td>(5.154)</td>
</tr>
<tr>
<td>Observations</td>
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<td>474</td>
<td>474</td>
<td>474</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.223</td>
<td>0.225</td>
<td>0.250</td>
<td>0.356</td>
</tr>
<tr>
<td>Number of Counties</td>
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<td>79</td>
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<tr>
<td>County FE</td>
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<td>X</td>
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<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Enrollment Pre-Policy Mean</td>
<td>37026</td>
<td>24584</td>
<td>17902</td>
<td>34421</td>
</tr>
</tbody>
</table>

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

Standard errors clustered at the county level

Note: This regression estimates the effect on the number of individuals enrolled in Delta Dental between ages 35 to 64 by parental status being in a county with a larger proportion of young adults in the population (calculated as the number of young adults between ages 20 and 24 in the county divided by the total county population). Observations are at the county-year level. I use a log-log specification to take into account that the county-level eligible ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Figure 7: Falsification Test: County-Level Standardized Distribution of Ratio of 30 to 34 Year Olds in 2011
Figure 8: Falsification Test: Testing for a Break in Trend in Coverage Rates

Impact on County-Level Coverage Rates (Percentage Changes)

Notes: As part of the falsification, I implement the parallel trends test to examine whether there are common trends between counties with larger and smaller non-eligible ratios in the pre-implementation period (2009 and 2010) relative to 2008, where the non-eligible ratios are given by the ratio of 30 to 34 year olds in the county population under age 65. Each dot represents the coefficient estimate for the given year, where the mapped coefficients are the interactions between the county-specific eligible ratio and the year fixed effects. 2008 is used as the excluded base year. The coefficients used in these graphs are the standardized coefficients for ease of interpretation. Additional control variables included in these regressions are such as the log of the size of the population without any form of insurance (between ages 18-64, and under age 19), the unemployment rate, and the number of dental offices per county. The 90% confidence intervals are given by the bars around each coefficient point estimate. Standard errors are clustered at the county-level, and observations are weighted by the size of the under 65 population in each county.
Table 13: Falsification Test: Unweighted Least Squares Regression of County Coverage Rates by Age Group on Ratio of 30-34 Year Olds in the Population (Log-Log)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(County Non-Eligible Ratio)*1(Post)</td>
<td>-0.0436</td>
<td>-0.195</td>
<td>-0.0911</td>
<td>-0.0595</td>
<td>-0.0682</td>
<td>-0.0945</td>
<td>-0.000377</td>
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<tr>
<td></td>
<td>(0.116)</td>
<td>(0.141)</td>
<td>(0.177)</td>
<td>(0.148)</td>
<td>(0.159)</td>
<td>(0.132)</td>
<td>(0.111)</td>
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<tr>
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<td>(0.955)</td>
<td>(1.159)</td>
<td>(1.179)</td>
<td>(1.166)</td>
<td>(1.516)</td>
<td>(1.398)</td>
<td>(0.907)</td>
</tr>
<tr>
<td>Observations</td>
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<td>474</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.228</td>
<td>0.152</td>
<td>0.140</td>
<td>0.214</td>
<td>0.409</td>
<td>0.097</td>
<td>0.251</td>
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<tr>
<td>Year FE</td>
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<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Level Pre-Policy Mean</td>
<td>0.244</td>
<td>0.190</td>
<td>0.204</td>
<td>0.199</td>
<td>0.146</td>
<td>0.175</td>
<td>0.269</td>
</tr>
<tr>
<td>Enrollment Share Mean</td>
<td>1</td>
<td>0.170</td>
<td>0.0695</td>
<td>0.0628</td>
<td>0.0458</td>
<td>0.0491</td>
<td>0.512</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Note: This regression estimates the effect on the coverage rate of each age group (calculated to be the number of individuals enrolled in Delta Dental plans in the county in the age group, divided by the total number of people in the age group in the county) from being in a county with a larger proportion of 30 to 34 year olds in the population. Observations are at the county-year level. I use a log-log specification to take into account that the distribution for the young adult ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Table 14: Falsification Test: Unweighted Least Squares Regression of Number of Enrolled by Age Group on Ratio of 30-34 Year Olds in the Population (Log-Log)

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(County Non-Eligible Ratio)*1(Post)</td>
<td>-0.140</td>
<td>-0.226</td>
<td>-0.0628</td>
<td>-0.0592</td>
<td>-0.0683</td>
<td>-0.0841</td>
<td>-0.0814</td>
</tr>
<tr>
<td></td>
<td>(0.123)</td>
<td>(0.152)</td>
<td>(0.169)</td>
<td>(0.147)</td>
<td>(0.162)</td>
<td>(0.130)</td>
<td>(0.123)</td>
</tr>
<tr>
<td>Constant</td>
<td>-13.74**</td>
<td>-5.350</td>
<td>0.236</td>
<td>6.080***</td>
<td>-2.589</td>
<td>-6.069**</td>
<td>-10.51*</td>
</tr>
<tr>
<td></td>
<td>(6.562)</td>
<td>(4.496)</td>
<td>(2.867)</td>
<td>(1.835)</td>
<td>(2.827)</td>
<td>(2.365)</td>
<td>(5.633)</td>
</tr>
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<td>474</td>
<td>474</td>
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</tr>
<tr>
<td>R-squared</td>
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<td>0.205</td>
<td>0.214</td>
<td>0.401</td>
<td>0.388</td>
<td>0.238</td>
<td>0.289</td>
</tr>
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<tr>
<td>Year FE</td>
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<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Level Pre-Policy Mean</td>
<td>138729</td>
<td>23879</td>
<td>9967</td>
<td>8148</td>
<td>5800</td>
<td>6808</td>
<td>72038</td>
</tr>
<tr>
<td>Enrollment Share Mean</td>
<td>0.170</td>
<td>0.0695</td>
<td>0.0628</td>
<td>0.0458</td>
<td>0.0491</td>
<td>0.512</td>
<td></td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Note: This regression estimates the effect on the number of individuals enrolled in Delta Dental for each age group from being in a county with a larger proportion of 30 to 34 year olds in the population. Observations are at the county-year level. I use a log-log specification to take into account that the distribution for the young adult ratio is skewed. Standard errors are clustered at the county level and are contained in parentheses.
Figure 9: Comparison Between Office-Specific and County Eligible Ratios

(a) Distribution of the Office-Level Eligible Ratio

![Market vs. County Eligible Ratio](image)

(b) Error Distribution from the Linear Prediction of Office-Specific on County-Specific Eligible Ratio

![Error Distribution](image)

Notes: Panel (a) maps the office-specific eligible ratio (also called market eligible ratio), constructed using the modified Elzinga-Hogarty approach to defining the market at the office level, to the original county-level eligible ratio. Panel (b) maps the error terms from the regression of the market eligible ratio on the county of operation eligible ratio to show that there is no clear direction to the bias from using the market definition provided by the Elzinga-Hogarty approach.
Figure 10: Office-Level Z-Score Distribution for the Office-Specific Eligible Ratio

Notes: This figure maps the standardized normal distribution, primarily to show where the data lies in number of standard deviations from the mean in the sample, using the High Population sample (greater than 250,000 individuals under age 65 in the market in 2011).
Table 15: Summary Statistics for Office-Level Subsamples

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Full Office Sample</th>
<th>(2) 250K Sample</th>
<th>(3) Self-Referral Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td># Patients 65</td>
<td>-73.84*** (-7.42)</td>
<td>-32.55** (-2.96)</td>
<td>-29.53* (-2.55)</td>
</tr>
<tr>
<td># Visits</td>
<td>-148.2*** (-5.51)</td>
<td>-41.22 (-1.39)</td>
<td>-45.74 (-1.44)</td>
</tr>
<tr>
<td># Tooth Fillings</td>
<td>-37.24*** (-4.13)</td>
<td>-4.363 (-0.44)</td>
<td>-11.94 (-1.10)</td>
</tr>
<tr>
<td># Surface 1 Fillings</td>
<td>-17.03*** (-3.90)</td>
<td>-1.115 (-0.22)</td>
<td>-6.741 (-1.29)</td>
</tr>
<tr>
<td># Surface 2 Fillings</td>
<td>-17.65*** (-4.94)</td>
<td>-7.350 (-1.91)</td>
<td>-8.482* (-2.02)</td>
</tr>
<tr>
<td># Surface 3 Fillings</td>
<td>-2.568 (-1.58)</td>
<td>0.862 (0.46)</td>
<td>0.716 (0.34)</td>
</tr>
<tr>
<td># Surface 4 Fillings</td>
<td>-0.0112 (-0.01)</td>
<td>3.169* (2.29)</td>
<td>2.726 (1.76)</td>
</tr>
<tr>
<td># Root Canals</td>
<td>1.639* (2.41)</td>
<td>1.269 (1.39)</td>
<td>0.989 (0.98)</td>
</tr>
<tr>
<td># Extractions</td>
<td>-1.661 (-1.28)</td>
<td>-3.645** (-2.68)</td>
<td>-5.499*** (-3.86)</td>
</tr>
<tr>
<td>N</td>
<td>2375</td>
<td>1482</td>
<td>1285</td>
</tr>
</tbody>
</table>

$t$ statistics in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Notes: This table implements t-tests comparing offices with an above median office-specific eligible ratio with those with an above median office-specific eligible ratio in each sample, with medians being specific to each office subsample. The variables are totals measured at the office-year level among patients under age 65. The full office sample is constructed of general offices operating in a Michigan county that are present for all years used in the analysis (2008-2013) with at least 10 continuously insured patients in each year. The high population sample is the subsample of offices with at least 250,000 individuals under age 65 in the market. The high referral sample is a subsample of the high population sample, comprised of offices that are observed to carry out at least one root canal during the entire time period.
Figure 11: Effect of Dependent Expansion Size on Office Load by Year, High Population Offices

Notes: The coefficients mapped in this figure represent the average impact of the expansion across all offices for each age group over the years 2009 to 2013 relative to 2008 as the base year, and are interpreted as the average percentage increase in the number of patients for an office from having a "high" office-specific eligible ratio in each year, where "high" in this context is taken to be in the topmost quartile of the distribution of office-specific eligible ratios. The coefficients are given by the dots, whereas the bars give the 90% confidence intervals around each point estimate and use standard errors that are clustered at the county-level. The sample used to generate this is the high population sample of offices, comprised of offices operating in markets with at least 250,000 individuals under age 65.
Table 16: Standardized Coefficients: Increase in Office Load Among Patients Under Age 65, Office-Level Regressions

<table>
<thead>
<tr>
<th>Log of Dependent Variable</th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(Office-Specific Eligible Ratio)*1(Post)</td>
<td>0.0360***</td>
<td>0.0330***</td>
</tr>
<tr>
<td></td>
<td>(0.00831)</td>
<td>(0.00786)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.030</td>
<td>0.039</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,285</td>
</tr>
<tr>
<td>Sample</td>
<td>250K</td>
<td>Self-Refer</td>
</tr>
<tr>
<td>County FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre-Policy Control Level Mean</td>
<td>289.1</td>
<td>294.1</td>
</tr>
<tr>
<td>First Stage F-Stat</td>
<td>18.77</td>
<td>17.62</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Notes: This table contains the standardized coefficient estimates for office-year level regressions with log of proxies for office load (given by number of patients among those under age 65) as the dependent variables and the interaction of the log of the size of the dependent expansion faced by each office (proxied by the office-specific eligible ratio) with year fixed effects as the key independent variables of interest. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. Observations are weighted by the Elzinga-Hogarty weighted mean population for each market to take into account that holding fixed the office-specific eligible ratio, offices in markets that are larger in population will face a larger shock to the number of patients seen within practices.
Table 17: Standardized Coefficients: Increase in Number of Visits Among Patients Under Age 65, Office-Level Regressions

<table>
<thead>
<tr>
<th>Log of Dependent Variable</th>
<th>(1) # Visits</th>
<th>(2) # Visits</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(Office-Specific Eligible Ratio)*1(Post)</td>
<td>0.0392***</td>
<td>0.0349***</td>
</tr>
<tr>
<td></td>
<td>(0.00787)</td>
<td>(0.00776)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.028</td>
<td>0.033</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,285</td>
</tr>
<tr>
<td>Sample</td>
<td>250K</td>
<td>Self-Refer</td>
</tr>
<tr>
<td>County FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Pre-Policy Control Level Mean</td>
<td>641</td>
<td>656.1</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Notes: This table contains the standardized coefficient estimates for office-year level regressions with log of proxies for office load (given by number of visits among patients under age 65) as the dependent variables and the interaction of the log of the size of the dependent expansion faced by each office (proxied by the office-specific eligible ratio) with year fixed effects as the key independent variables of interest. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. Observations are weighted by the Elzinga-Hogarty weighted mean population for each market to take into account that holding fixed the office-specific eligible ratio, offices in markets that are larger in population will face a larger shock to the number of patients seen within practices.
Table 18: Age Group Breakdown of Increase in Office Load Among Patients Under Age 65, Office-Level Regressions, High Population Offices

<table>
<thead>
<tr>
<th>Log of Num Patients in Age Group</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1(Office-Specific Eligible Ratio)*1(Post)</td>
<td>0.0364***</td>
<td>0.0357***</td>
<td>0.0222</td>
<td>0.0351***</td>
</tr>
<tr>
<td></td>
<td>(0.00710)</td>
<td>(0.00804)</td>
<td>(0.0202)</td>
<td>(0.00690)</td>
</tr>
<tr>
<td>Constant</td>
<td>4.184</td>
<td>3.361</td>
<td>6.678</td>
<td>5.236</td>
</tr>
<tr>
<td></td>
<td>(2.936)</td>
<td>(4.193)</td>
<td>(3.857)</td>
<td>(3.611)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.040</td>
<td>0.014</td>
<td>0.027</td>
<td>0.031</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Year FE</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Pre-Policy Control Level Mean</td>
<td>40.16</td>
<td>36.25</td>
<td>23.82</td>
<td>169.5</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Notes: This table contains the standardized coefficient estimates for office-year level regressions with log of proxies for office load (given by number of patients and number of visits among those under age 65) as the dependent variables and the interaction of the log of the size of the dependent expansion faced by each office (proxied by the office-specific eligible ratio) with year fixed effects as the key independent variables of interest. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. Observations are weighted by the Elzinga-Hogarty weighted mean population for each market to take into account that holding fixed the office-specific eligible ratio, offices in markets that are larger in population will face a larger shock to the number of patients seen within practices.
Table 19: Age Group Breakdown of Increase in Office Load Among New Patients Under Age 65, Office-Level Regressions, High Population Offices

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>&lt;65</th>
<th>0-14</th>
<th>15-24</th>
<th>25-34</th>
<th>Dep 0-17</th>
<th>Dep 18-26</th>
<th>No Dep</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Office-Specific Eligible Ratio)*1(Post)</td>
<td>0.0294</td>
<td>0.0126</td>
<td>0.0423*</td>
<td>0.0291</td>
<td>0.0263</td>
<td>0.0404*</td>
<td>0.0164</td>
</tr>
<tr>
<td>(0.0178)</td>
<td>(0.0197)</td>
<td>(0.0204)</td>
<td>(0.0175)</td>
<td>(0.0173)</td>
<td>(0.0209)</td>
<td>(0.0137)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,250</td>
<td>8,250</td>
<td>8,250</td>
<td>8,250</td>
<td>8,250</td>
<td>8,250</td>
<td>8,250</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.030</td>
<td>0.024</td>
<td>0.014</td>
<td>0.023</td>
<td>0.014</td>
<td>0.016</td>
<td>0.019</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1.375</td>
<td>1.375</td>
<td>1.375</td>
<td>1.375</td>
<td>1.375</td>
<td>1.375</td>
<td>1.375</td>
</tr>
<tr>
<td>Sample</td>
<td>250K</td>
<td>250K</td>
<td>250K</td>
<td>250K</td>
<td>250K</td>
<td>250K</td>
<td>250K</td>
</tr>
<tr>
<td>County FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Year FE</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Weighting</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>Pre-Policy Control Level Mean</td>
<td>40.52</td>
<td>7.400</td>
<td>5.282</td>
<td>4.938</td>
<td>7.327</td>
<td>4.753</td>
<td>9.266</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Notes: This table contains the coefficient estimates for office-year level regressions with log of proxies for office load (given by number of new patients in each age group) as the dependent variables and the interaction of the log of the size of the dependent expansion faced by each office (proxied by the office-specific eligible ratio) with year fixed effects as the key independent variables of interest. The sample used is the High Population office sample (greater than 250,000 people under age 65 in the market population) after removing offices in the lower and upper 5% of the distribution in the minimum number of new patients per year across all years of the sample. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. Observations are weighted by the Elzinga-Hogarty weighted mean population for each market to take into account that holding fixed the office-specific eligible ratio, offices in markets that are larger in population will face a larger shock to the number of patients seen within practices.
Table 20: OLS Regressions: Positive Correlations Between Average Number of Cavity Treatments Per Patient and Office Load

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0279***</td>
<td>0.0164***</td>
<td>0.00872</td>
<td>0.00587</td>
<td>0.00281</td>
<td>9.43e-05</td>
<td>-0.00655</td>
</tr>
<tr>
<td></td>
<td>(0.00424)</td>
<td>(0.00456)</td>
<td>(0.00496)</td>
<td>(0.00387)</td>
<td>(0.00217)</td>
<td>(0.00121)</td>
<td>(0.00625)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.049</td>
<td>0.053</td>
<td>0.018</td>
<td>0.008</td>
<td>0.005</td>
<td>0.019</td>
<td>0.022</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0645</td>
<td>0.0373</td>
<td>0.0657</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
</tr>
</tbody>
</table>

Notes: This table contains the coefficient estimates for office-year level regressions with log of the number of restorative procedures (by type) averaged among all patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used for these regressions is the 250K sample, comprised of offices operating in markets with at least 250,000 individuals under age 65 in the market population. Standard errors are clustered at the county level.
Table 21: OLS Regression: Relationship Between Office Load and Average Number of Visits Per Patient and Average Yearly Payment

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Visits</th>
<th>(2) Routine Visits</th>
<th>(3) Plan Pay</th>
<th>(4) Patient Pay</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0874***</td>
<td>0.0398***</td>
<td>0.317***</td>
<td>-0.0177</td>
</tr>
<tr>
<td></td>
<td>(0.00912)</td>
<td>(0.00895)</td>
<td>(0.0585)</td>
<td>(0.0210)</td>
</tr>
<tr>
<td>Constant</td>
<td>0.724**</td>
<td>-0.206</td>
<td>5.927***</td>
<td>3.594***</td>
</tr>
<tr>
<td></td>
<td>(0.289)</td>
<td>(0.801)</td>
<td>(1.907)</td>
<td>(0.707)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.132</td>
<td>0.032</td>
<td>0.210</td>
<td>0.008</td>
</tr>
<tr>
<td>Number of groupoffice</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2.278</td>
<td>1.985</td>
<td>389.1</td>
<td>194.3</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Notes: This table contains the coefficient estimates for office-year level regressions with log of the number of visits (by type) and yearly payment amounts (for insurers and patients) averaged among all patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used for these regressions is the 250K sample, comprised of offices operating in markets with at least 250,000 individuals under age 65 in the market population. Standard errors are clustered at the county level.
Table 22: OLS Regression: Relationship Between Office Load and Average Number of Routine Procedures Per Patient

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Oral Evaluations</th>
<th>(2) Cleanings</th>
<th>(3) Diagnostic Imaging</th>
<th>(4) Fluoride Txt</th>
<th>(5) Sealants</th>
<th>(6) Hygiene Instrucs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.016</td>
<td>0.085</td>
<td>0.034</td>
<td>0.081</td>
<td>0.004</td>
<td>0.002</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.127</td>
<td>1.269</td>
<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
</tr>
</tbody>
</table>

Notes: This table contains the coefficient estimates for office-year level regressions with log of the number of preventive and routine procedures (by type) averaged among all patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used for these regressions is the 250K sample, comprised of offices operating in markets with at least 250,000 individuals under age 65 in the market population. Standard errors are clustered at the county level.
Table 23: Effect of Increase in Number of Patients from Dependent Expansion on Average Yearly Frequency and Average Yearly Cost of Care for Continuously Insured Patients, High Population Sample

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.123***</td>
<td>0.0868***</td>
<td>0.481***</td>
<td>0.332**</td>
</tr>
<tr>
<td></td>
<td>(0.0140)</td>
<td>(0.0217)</td>
<td>(0.0811)</td>
<td>(0.115)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.180</td>
<td>0.066</td>
<td>0.239</td>
<td>0.066</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2.278</td>
<td>1.985</td>
<td>389.1</td>
<td>194.3</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0607</td>
<td>0.0240</td>
<td>0.0966</td>
<td>0.0678</td>
</tr>
<tr>
<td></td>
<td>(0.0496)</td>
<td>(0.0220)</td>
<td>(0.143)</td>
<td>(0.191)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.113</td>
<td>0.032</td>
<td>0.087</td>
<td>0.026</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2.278</td>
<td>1.985</td>
<td>389.1</td>
<td>194.3</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
</tr>
<tr>
<td>First Stage F-stat</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of visits (by type), average yearly insurer reimbursement, and average yearly out-of-pocket patient cost among all patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the high population sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 24: The Effect of Change in Office Size on Average # Routine Procedures Per Continuously Insured (2008-2013) Patient Among High Population Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>Oral Evaluations</th>
<th>Cleanings</th>
<th>Diagnostic Imaging</th>
<th>Fluoride Txt</th>
<th>Sealants</th>
<th>Hygiene Instrucs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0202**</td>
<td>0.0742***</td>
<td>0.0985***</td>
<td>0.0357***</td>
<td>0.00339**</td>
<td>0.00137</td>
</tr>
<tr>
<td>(0.00763)</td>
<td>(0.00616)</td>
<td>(0.0155)</td>
<td>(0.00629)</td>
<td>(0.00156)</td>
<td>(0.0016)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.041</td>
<td>0.107</td>
<td>0.053</td>
<td>0.099</td>
<td>0.006</td>
<td>0.002</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.127</td>
<td>1.269</td>
<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>Oral Evaluations</th>
<th>Cleanings</th>
<th>Diagnostic Imaging</th>
<th>Fluoride Txt</th>
<th>Sealants</th>
<th>Hygiene Instrucs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0856</td>
<td>-0.0163</td>
<td>0.158</td>
<td>0.0201</td>
<td>0.0436</td>
<td>0.0341***</td>
</tr>
<tr>
<td>(0.0731)</td>
<td>(0.0453)</td>
<td>(0.105)</td>
<td>(0.0589)</td>
<td>(0.0366)</td>
<td>(0.00780)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
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<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>-0.049</td>
<td>-0.037</td>
<td>0.025</td>
<td>0.016</td>
<td>-0.029</td>
<td>-0.276</td>
</tr>
<tr>
<td>Number of Offices</td>
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<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.127</td>
<td>1.269</td>
<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
</tr>
<tr>
<td>First Stage F-stat</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level

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

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of routine procedures by type among continuously insured patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the high population sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 25: The Effect of Change in Office Size on Average # Cavity Procedures Per Continuously Insured (2008-2013) Patient Among High Population Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>Cavities</th>
<th>Surface 1</th>
<th>Surface 2</th>
<th>Surface 3</th>
<th>4+ Surfaces</th>
<th>Root Canals</th>
<th>Extractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0388*** (0.00748)</td>
<td>0.0153*** (0.00329)</td>
<td>0.0195*** (0.00307)</td>
<td>0.00521 (0.00307)</td>
<td>0.00315 (0.00233)</td>
<td>-0.00103 (0.000853)</td>
<td>0.00172 (0.00197)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.039</td>
<td>0.032</td>
<td>0.016</td>
<td>0.006</td>
<td>0.006</td>
<td>0.009</td>
<td>0.008</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
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<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0645</td>
<td>0.0373</td>
<td>0.0657</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level
*** p<0.01, ** p<0.05, * p<0.1

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>Cavities</th>
<th>Surface 1</th>
<th>Surface 2</th>
<th>Surface 3</th>
<th>4+ Surfaces</th>
<th>Root Canals</th>
<th>Extractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.00443 (0.01425)</td>
<td>0.0633** (0.03191)</td>
<td>0.0228 (0.01971)</td>
<td>-0.0382*** (0.01014)</td>
<td>-0.0301*** (0.00524)</td>
<td>0.0122 (0.0244)</td>
<td>-0.0362 (0.0391)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.001</td>
<td>-0.012</td>
<td>0.004</td>
<td>-0.033</td>
<td>-0.025</td>
<td>-0.010</td>
<td>-0.025</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
<td>1,482</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0645</td>
<td>0.0373</td>
<td>0.0657</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
<td>131.7</td>
</tr>
<tr>
<td>First Stage F-stat</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of cavity procedures by type among continuously insured patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the high population sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 26: The Effect of Change in Office Size on Average Yearly Frequency and Average Yearly Cost of Care Per Continuously Insured (2008-2013) Patient Among Self Referral Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Visits</td>
<td>Routine Visits</td>
<td>Plan Pay</td>
<td>Patient Pay</td>
</tr>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.119***</td>
<td>0.0824***</td>
<td>0.463***</td>
<td>0.285</td>
</tr>
<tr>
<td></td>
<td>(0.0205)</td>
<td>(0.0233)</td>
<td>(0.116)</td>
<td>(0.169)</td>
</tr>
<tr>
<td>Observations</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.161</td>
<td>0.056</td>
<td>0.221</td>
<td>0.052</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2.927</td>
<td>1.972</td>
<td>400.3</td>
<td>199.7</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level
*** p<0.01, ** p<0.05, * p<0.1

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Visits</td>
<td>Routine Visits</td>
<td>Plan Pay</td>
<td>Patient Pay</td>
</tr>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0251</td>
<td>0.0526</td>
<td>0.0213</td>
<td>-0.0928</td>
</tr>
<tr>
<td></td>
<td>(0.0523)</td>
<td>(0.0422)</td>
<td>(0.179)</td>
<td>(0.193)</td>
</tr>
<tr>
<td>Observations</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.052</td>
<td>0.048</td>
<td>0.025</td>
<td>-0.030</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2.297</td>
<td>1.972</td>
<td>400.3</td>
<td>199.7</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
</tr>
<tr>
<td>First Stage F-stat</td>
<td>17.62</td>
<td>17.62</td>
<td>17.62</td>
<td>17.62</td>
</tr>
</tbody>
</table>

Standard errors clustered at the county level
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of visits (by type), average yearly insurer reimbursement, and average yearly out-of-pocket patient cost among continuously insured patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011 with at least one root canal procedure during the time period (2008-2013). Standard errors are clustered at the county level.
Table 27: The Effect of Change in Office Size on Average # Routine Procedures Per Continuously Insured (2008-2013) Patient Among Self Referral Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>Oral Evaluations</th>
<th>Cleanings</th>
<th>Diagnostic Imaging</th>
<th>Fluoride Txt</th>
<th>Sealants</th>
<th>Hygiene Instrucs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0236** (0.00841)</td>
<td>0.0747*** (0.00545)</td>
<td>0.104*** (0.0194)</td>
<td>0.0416*** (0.00735)</td>
<td>0.00511** (0.00192)</td>
<td>0.00174 (0.00132)</td>
</tr>
<tr>
<td>Observations</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.046</td>
<td>0.102</td>
<td>0.052</td>
<td>0.107</td>
<td>0.006</td>
<td>0.002</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.132</td>
<td>1.261</td>
<td>1.367</td>
<td>0.266</td>
<td>0.0409</td>
<td>0.00116</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
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</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>Oral Evaluations</th>
<th>Cleanings</th>
<th>Diagnostic Imaging</th>
<th>Fluoride Txt</th>
<th>Sealants</th>
<th>Hygiene Instrucs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0107 (0.0018)</td>
<td>-0.0377 (0.0536)</td>
<td>0.210*** (0.103)</td>
<td>-0.00803 (0.0612)</td>
<td>0.0166 (0.0270)</td>
<td>0.0456*** (0.0124)</td>
</tr>
<tr>
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<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>-0.073</td>
<td>-0.090</td>
<td>-0.001</td>
<td>-0.009</td>
<td>-0.001</td>
<td>-0.485</td>
</tr>
<tr>
<td>County FE</td>
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<td>YES</td>
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<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
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<tr>
<td>Level Mean</td>
<td>0.132</td>
<td>1.261</td>
<td>1.367</td>
<td>0.266</td>
<td>0.0409</td>
<td>0.00116</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
</tr>
</tbody>
</table>

First Stage F-stat | 17.62 | 17.62 | 17.62 | 17.62 | 17.62 | 17.62 |

Standard errors clustered at the county level

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of routine procedures by type among continuously insured patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011 with at least one root canal procedure during the time period (2008-2013). Standard errors are clustered at the county level.
Table 28: The Effect of Change in Office Size on Average # Cavity Procedures Per Continuously Insured (2008-2013) Patient Among Self-Referral Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>(1) Cavities</th>
<th>(2) Surface 1</th>
<th>(3) Surface 2</th>
<th>(4) Surface 3</th>
<th>(5) 4+ Surfaces</th>
<th>(6) Root Canals</th>
<th>(7) Extractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0456*** (0.0104)</td>
<td>0.0195*** (0.00329)</td>
<td>0.0229*** (0.00617)</td>
<td>0.00623 (0.00433)</td>
<td>0.00375 (0.00252)</td>
<td>-0.000727 (0.000946)</td>
<td>0.00340** (0.00121)</td>
</tr>
<tr>
<td>Observations</td>
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<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.043</td>
<td>0.034</td>
<td>0.019</td>
<td>0.007</td>
<td>0.007</td>
<td>0.010</td>
<td>0.011</td>
</tr>
<tr>
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<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.753</td>
<td>0.310</td>
<td>0.256</td>
<td>0.119</td>
<td>0.0678</td>
<td>0.0433</td>
<td>0.0692</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>(1) Cavities</th>
<th>(2) Surface 1</th>
<th>(3) Surface 2</th>
<th>(4) Surface 3</th>
<th>(5) 4+ Surfaces</th>
<th>(6) Root Canals</th>
<th>(7) Extractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>-0.111 (0.0837)</td>
<td>0.0292 (0.0602)</td>
<td>-0.0307 (0.0510)</td>
<td>-0.0626*** (0.0212)</td>
<td>-0.0823*** (0.0158)</td>
<td>0.0139 (0.0308)</td>
<td>-0.0582 (0.0558)</td>
</tr>
<tr>
<td>Observations</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
<td>7,710</td>
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<tr>
<td>R-squared</td>
<td>-0.071</td>
<td>0.002</td>
<td>-0.019</td>
<td>-0.075</td>
<td>-0.157</td>
<td>-0.010</td>
<td>-0.061</td>
</tr>
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<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
<td>1,285</td>
</tr>
<tr>
<td>County FE</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.753</td>
<td>0.310</td>
<td>0.256</td>
<td>0.119</td>
<td>0.0678</td>
<td>0.0433</td>
<td>0.0692</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
<td>134.1</td>
</tr>
</tbody>
</table>

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of cavity procedures by type among continuously insured patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011 with at least one root canal procedure during the time period (2008-2013). Standard errors are clustered at the county level.
Table 29: The Effect of Change in Office Size on Average Yearly Frequency and Average Yearly Cost of Care Per Continuously Insured and Continuously Seen (2008-2013) Patient Among High Population Offices

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Visits</td>
<td>Routine Visits</td>
<td>Plan Pay</td>
<td>Patient Pay</td>
</tr>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0781***</td>
<td>0.0264*</td>
<td>0.145*</td>
<td>-0.0410</td>
</tr>
<tr>
<td></td>
<td>(0.0110)</td>
<td>(0.0146)</td>
<td>(0.0706)</td>
<td>(0.0499)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.108</td>
<td>0.008</td>
<td>0.037</td>
<td>0.020</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
</tr>
<tr>
<td>County FE</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2,278</td>
<td>1,985</td>
<td>389.1</td>
<td>194.3</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
</tr>
</tbody>
</table>

Panel B: IV Regression

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Visits</td>
<td>Routine Visits</td>
<td>Plan Pay</td>
<td>Patient Pay</td>
</tr>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0599***</td>
<td>0.0762***</td>
<td>0.148</td>
<td>0.0492</td>
</tr>
<tr>
<td></td>
<td>(0.0222)</td>
<td>(0.0266)</td>
<td>(0.0913)</td>
<td>(0.124)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.026</td>
<td>-0.006</td>
<td>0.017</td>
<td>-0.001</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,471</td>
<td>1,471</td>
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<td>1,471</td>
</tr>
<tr>
<td>County FE</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>2,278</td>
<td>1,985</td>
<td>389.1</td>
<td>194.3</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
</tr>
<tr>
<td>First Stage F-stat</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
</tr>
</tbody>
</table>

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of visits (by type), average yearly insurer reimbursement, and average yearly out-of-pocket patient cost among continuously insured and continuously seen (at least one visit per year in the dental office) patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 30: The Effect of Change in Office Size on Average # Cavity Procedures Per Continuously Insured and Continuously Seen (2008-2013) Patient Among High Population Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>Cavities</th>
<th>Surface 1</th>
<th>Surface 2</th>
<th>Surface 3</th>
<th>4+ Surfaces</th>
<th>Root Canals</th>
<th>Extractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>-0.0242 (0.0171)</td>
<td>-0.0166 (0.0130)</td>
<td>-0.0101 (0.0155)</td>
<td>-0.0160** (0.00564)</td>
<td>-0.00133 (0.00324)</td>
<td>-0.00498* (0.00254)</td>
<td>-0.00477 (0.00283)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
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</tr>
<tr>
<td>R-squared</td>
<td>0.050</td>
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<td>0.024</td>
<td>0.009</td>
<td>0.008</td>
<td>0.007</td>
<td>0.012</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
</tr>
<tr>
<td>County FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0645</td>
<td>0.0373</td>
<td>0.0657</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>Cavities</th>
<th>Surface 1</th>
<th>Surface 2</th>
<th>Surface 3</th>
<th>4+ Surfaces</th>
<th>Root Canals</th>
<th>Extractions</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>-0.149** (0.0636)</td>
<td>-0.0602 (0.0731)</td>
<td>-0.0392* (0.0201)</td>
<td>-0.0625** (0.0278)</td>
<td>-0.00778 (0.00953)</td>
<td>0.0121 (0.0187)</td>
<td>-0.0226 (0.0290)</td>
</tr>
<tr>
<td>Observations</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
</tr>
<tr>
<td>R-squared</td>
<td>-0.015</td>
<td>-0.003</td>
<td>-0.002</td>
<td>-0.009</td>
<td>0.001</td>
<td>-0.003</td>
<td>-0.001</td>
</tr>
<tr>
<td>Number of Offices</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
<td>1,471</td>
</tr>
<tr>
<td>County FE</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0645</td>
<td>0.0373</td>
<td>0.0657</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
<td>76</td>
</tr>
<tr>
<td>First Stage F-stat</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
<td>20.88</td>
</tr>
</tbody>
</table>

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of cavity procedures by type among continuously insured and continuously seen (at least one visit per year in the dental office) patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 31: The Effect of Change in Office Size on Average # Routine Procedures Per Continuously Insured and Continuously Seen (2008-2013) Patient Among High Population Offices

<table>
<thead>
<tr>
<th>Panel A: OLS Regression</th>
<th>Oral Evaluations</th>
<th>Cleanings</th>
<th>Diagnostic Imaging</th>
<th>Fluoride Txt</th>
<th>Sealants</th>
<th>Hygiene Instruc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>-0.0324***</td>
<td>0.0728***</td>
<td>0.0666***</td>
<td>0.0177**</td>
<td>-0.00322</td>
<td>0.00333*</td>
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<tr>
<td>(0.00752)</td>
<td>(0.0118)</td>
<td>(0.0168)</td>
<td>(0.00712)</td>
<td>(0.00237)</td>
<td>(0.00164)</td>
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</tr>
<tr>
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<td>8,826</td>
<td>8,826</td>
<td>8,826</td>
</tr>
<tr>
<td>R-squared</td>
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<td>0.092</td>
<td>0.026</td>
<td>0.114</td>
<td>0.015</td>
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</tr>
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<td>YES</td>
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<td>Level Mean</td>
<td>0.127</td>
<td>1.269</td>
<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
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<td>76</td>
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</table>

<table>
<thead>
<tr>
<th>Panel B: IV Regression</th>
<th>Oral Evaluations</th>
<th>Cleanings</th>
<th>Diagnostic Imaging</th>
<th>Fluoride Txt</th>
<th>Sealants</th>
<th>Hygiene Instruc</th>
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</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
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<td>0.00988</td>
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<td>(0.0699)</td>
<td>(0.0579)</td>
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<td>8,826</td>
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<td>8,826</td>
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<tr>
<td>R-squared</td>
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<tr>
<td>Level Mean</td>
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<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>76</td>
<td>76</td>
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<td>First Stage F-stat</td>
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<td>20.88</td>
<td>20.88</td>
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</tbody>
</table>

Standard errors clustered at the county level

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

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of routine procedures by type among continuously insured and continuously seen (at least one visit per year in the dental office) patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 32: The Effect of Change in Office Size on Average # Routine Procedures Per Patient Among High Population Offices

<table>
<thead>
<tr>
<th>VARIABLES</th>
<th>(1) Oral Evaluations</th>
<th>(2) Cleanings</th>
<th>(3) Diagnostic Imaging</th>
<th>(4) Fluoride Txt</th>
<th>(5) Sealants</th>
<th>(6) Hygiene Instrucs</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
<td>0.0290***</td>
<td>0.0618***</td>
<td>0.0700***</td>
<td>0.0320***</td>
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<tr>
<td></td>
<td>(0.00529)</td>
<td>(0.0109)</td>
<td>(0.00812)</td>
<td>(0.00810)</td>
<td>(0.00278)</td>
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</tr>
<tr>
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<td>8,892</td>
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<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.016</td>
<td>0.085</td>
<td>0.034</td>
<td>0.081</td>
<td>0.004</td>
<td>0.002</td>
</tr>
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<td>1,482</td>
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<tr>
<td>Office FE</td>
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<td>YES</td>
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</tr>
<tr>
<td>Level Mean</td>
<td>0.127</td>
<td>1.269</td>
<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
</tr>
<tr>
<td></td>
<td>(1) Oral Evaluations</td>
<td>(2) Cleanings</td>
<td>(3) Diagnostic Imaging</td>
<td>(4) Fluoride Txt</td>
<td>(5) Sealants</td>
<td>(6) Hygiene Instrucs</td>
</tr>
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<td>Log(Num Patients Under Age 65)</td>
<td>0.00128</td>
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<td>(0.0577)</td>
<td>(0.0819)</td>
<td>(0.0767)</td>
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<td>8,892</td>
<td>8,892</td>
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<tr>
<td>R-squared</td>
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<td>1,482</td>
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<td>Office FE</td>
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<td>YES</td>
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</tr>
<tr>
<td>Level Mean</td>
<td>0.127</td>
<td>1.269</td>
<td>1.346</td>
<td>0.264</td>
<td>0.0422</td>
<td>0.00197</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
</tr>
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<td>First Stage F-stat</td>
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<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
<td>18.77</td>
</tr>
</tbody>
</table>

Robust standard errors in parentheses

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

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of routine procedures by type among all patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. The sample used here is the self-referral sample, comprised of offices with at least 250,000 individuals under age 65 in the market in 2011. Standard errors are clustered at the county level.
Table 33: The Effect of Change in Office Size on Average # Cavity Procedures Per Patient Among High Population Offices

<table>
<thead>
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<th>VARIABLES</th>
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<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
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</thead>
<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
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<td>8,892</td>
<td>8,892</td>
</tr>
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</tr>
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<td>YES</td>
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<td>YES</td>
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<td>YES</td>
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<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0615</td>
<td>0.0373</td>
<td>0.0657</td>
</tr>
<tr>
<td>Avg # Patients in Group</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
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</table>

<table>
<thead>
<tr>
<th>VARIABLES</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
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<tbody>
<tr>
<td>Log(Num Patients Under Age 65)</td>
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<td>-0.0300</td>
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<td>(0.0132)</td>
<td>(0.0464)</td>
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<td>8,892</td>
<td>8,892</td>
<td>8,892</td>
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</tr>
<tr>
<td>R-squared</td>
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<td>-0.019</td>
<td>-0.029</td>
<td>-0.005</td>
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<td>1.482</td>
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<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Office FE</td>
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<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
<td>YES</td>
</tr>
<tr>
<td>Level Mean</td>
<td>0.734</td>
<td>0.306</td>
<td>0.249</td>
<td>0.114</td>
<td>0.0615</td>
<td>0.0373</td>
<td>0.0657</td>
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<tr>
<td>Avg # Patients in Group</td>
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<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
<td>296.6</td>
</tr>
</tbody>
</table>

First Stage F-stat 14

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Notes: This table contains the coefficient estimates for office-year level regressions with log of the average number of cavity procedures by type among all patients under age 65 in the practice as the dependent variables and the log of the number of patients under age 65 as the key independent variable of interest as a proxy for office load. Year and county fixed effects are incorporated into all regressions, as well as time-varying controls for the size of the population without any form of insurance (between ages 18-64, and under age 19) and the unemployment rate in the market. Including time-varying county characteristics do not substantially impact the regression results, and so are excluded here. Standard errors are clustered at the county level.
In the 1970s, a time when enrollment in employer-sponsored dental benefits were beginning to increase, and economists began to be concerned about the cost of dental benefits with the observed increase in medical expenditures, Bailit et al. (1979) writes:

...it must be remembered that a major objective of dental insurance should be to improve oral health... From an economic point of view, the problem can be stated in terms of the marginal return in dental health that can be achieved with greater investment in dental services, i.e., there comes a point where further investment in dental services produces very little increase in oral health. The problem, then, is identifying that level of investment where the marginal costs equal the marginal benefits in health. Furthermore, it is not only how much money is spent for dental services that matters but also the specific services which are purchased. In terms of improving health, some services may have greater benefit than others.

However, the predicted increase in dental expenditures has not played out as dramatically as would have been predicted in the 70s (which perhaps was a reason why economists turned away from studying the dental market) [CITE]. Furthermore, Section 2.3 is in direct opposition to this perception of dental insurance, suggesting that not only is there incentive for dental providers to induce demand, but that the incentives for demand inducement are exaggerated due to the failure to align payment for dental procedures with clinical outcomes for care. This section then discusses why such a payment system has arisen in dental insurance, and how to redesign dental insurance in the context of the optimal insurance literature.
5.1. Current Dental Insurance

Dental insurance is not insurance in the traditional sense - rather than providing coverage for low-risk, high-expenditure oral health events, the structure of dental insurance is instead that of a pre-payment plan for a set of common routine dental procedures that are generally seen to be preventive. However, Section 2.3 stressed that the common dental procedures covered by dental insurance have not been demonstrated to be efficacious nor cost-effective. In contrast, there are several preventive dental procedures with strong evidence bases for efficacy that are typically not covered as generously as routine procedures. If the goal of dental insurance is to increase oral health, why would these procedures go uncovered?

The simple answer is that dental insurers are not incentivized to improve oral health, and thus do not have a significant incentive to generously cover the effective preventive dental procedures especially if consumers do not demand them (either because their providers do not suggest these procedures to them, or because consumers are not aware of these procedures).

Dental insurers are not incentivized to improve oral health because they do not face the costs from catastrophic oral health events. As a result, dental insurance plans have costs that can be predicted accurately and planned for (Guay, 2006), and do not vary with the underlying dental risk or oral health status of the consumer. Because there is no tie between the costs of running a dental insurance plan and the risk and health of enrolled individuals, dental insurers have no incentive to cover procedures that will decrease the probability of adverse events or improve patient health. Instead, the catastrophic dental costs are turned over in extreme cases to health insurers, emergency rooms, or absorbed by the patient in out-of-pocket costs (Mertz, 2016).

Dental insurance became an attractive product for insurers to sell because of the predictable costs and after realizing that many who enroll would not seek care (Mertz, 2016). The predictability of costs in a dental insurance plan may then have been a barrier to adopting
capitation payment structures in dentistry, which were strongly recommended as early as 1980 in an IOM report (Mertz, 2016) but has yet to appear more than marginally outside of Medicaid. Furthermore, employer-sponsored dental insurance allows individuals to redirect their income via pretax payment towards routine dental care. In addition, dental insurers may be able to leverage the higher numbers of individuals enrolled in the plan to bargain prices with individual dentists to be lower than if patients directly bargained with dentists themselves on average. As a result, dental insurance would allow consumers to pre-purchase a routine set of dental services using pre-tax income and at possibly a lower price due to the increased bargaining power of the insurer.

Hence, dental insurers would only be incentivized to change the bundle of dental services to favor the clinically supported preventive dental procedures offered in dental plans if consumers valued the preventive procedures enough. Via Summers (1989), benefits will be provided up to the point where an extra dollar spent on including the service is valued by the enrollee at one dollar. However, oral health promotion studies have stressed that the use of preventive dental procedures depends whether patients receive advice from their dentist or dental staff to use these procedures (Mejia et al., 2011). There has been some preliminary work to show that there is no significant correlation between oral health literacy and use of preventive dental care (Burgette et al., 2015), though this is still an understudied area. As a result, due to the overall financial disincentive for providers to encourage or educate patients about effective preventive procedures, patients likely do not value or demand coverage for preventive services. ¹

However, there may be substantive medical savings generated by providing effective preventive dental care. For instance, diabetes is associated with increased occurrence and progression of oral complications and though the correlation seems to stem from a bidirectional relationship between diabetes and periodontal infection, there are a number of

¹Despite this, there are some dental insurers that have moved towards piloting several pay-for-performance initiatives to incentivize dentists to increase provision of preventive procedures proven to be clinically effective. For instance, Delta Dental of Massachusetts introduced a program to incentivize dental providers to place sealants soon after tooth eruption among children (Hunt and Aravamudhan, 2014)/
studies indicating that management and treatment of periodontal disease in patients may improve diabetic patients' glycemic levels and insulin requirements. Using linked medical and dental claims from 2001-2002, Albert et al. (2006) finds that individuals with more severe dental conditions had significantly higher medical costs, though endogeneity and self-selection into the sample and into treatment for the different dental conditions (which were proxies for having a dental condition) were undoubtedly a limitation of the study design. Avalere Health (2016) used the 2010 Chronic Condition Public Use Files from CMS to simulate the effects of covering the initial and follow-up treatment of periodontal disease for beneficiaries with diabetes or heart disease and those who had suffered a stroke, assuming that those receiving periodontal treatment would have decreased medical costs, finding overall cost-savings to Medicare of $63.5 billion from 2016 to 2025 primarily through reduced hospitalizations and emergency room visits. It is notable that periodontal treatment alone, which works to treat an existing infection, could be estimated to decrease medical costs to this extent, suggesting that there may be additional cost savings from providing preventive dental care earlier. In the Avalere analysis, the average allowed rate for initial periodontal treatment and ongoing maintenance every six months from private insurers were used to estimate the cost to Medicare of providing periodontal benefits. These were very high compared to the cost of providing treatment for preventive dental care - $825 for initial treatment procedures per person and $250 for ongoing maintenance every six months. Though these are suggestive results, I stress also that the literature in this area has room for growth - the vast majority of this literature uncovers correlations that cannot be interpreted causally.

There are other sources of low-hanging fruit in terms of how and why improving provision and/or coverage of preventive dental care may decrease medical costs. This is especially clear for emergency room and hospital admissions due to dental problems. Meyer and Tolleson-Rinehart (2016) writes that

---

2Albert et al. (2006) contains a brief literature review on this topic.
In 2012 [ED dental visits financed by Medicaid or self-paying patients] accounted for nearly 2 percent of all ED visits, consumed $1.6 billion - roughly 3 percent of all ED expenditures - and averaged $749 per visit. Similarly, dental visits to the ED cost $23 million in Georgia in 2007 and nearly $88 million in Florida in 2010. It is estimated that 79 percent of ED dental visits could be avoided if preventive care were more routine, translating to as much as $4 million savings to a single state Medicaid program.

The amount of savings is not likely to be overexaggerated - in Iowa, 78% of costs for restorative dental care for Medicaid children were attributable to hospital and anesthesiologist charges alone (Mouradian et al., 2000), with an average overall cost to Medicaid of $2009 per case. Similarly, in Louisiana, children receiving dental care in a hospital operating room incurred estimated costs of $1508, in contrast to $104 for children receiving outpatient dental care (Mouradian et al., 2000).

A recent study paints an even starker picture. Bruen et al. (2016) found that 98% of surgical care for Medicaid children under age 20 was due to treatment of dental caries, accounting for 26,373 cases across six states in 2011 and accounting for $68 million in total Medicaid payments in those six states. The six states included in the analysis had complete Medicaid data for both fee-for-service and capitated managed care in 2011. Extrapolating to the rest of the United States, Bruen et al. (2016) suggest that approximately $450 million in additional expenditures took place in 2011 due to surgical care for preventable pediatric dental conditions. Though this was a study focused on Medicaid, this suggests that failing to treat and prevent dental caries may lead to large medical expenses for insurers, patients, and the public health safety net.

Failure to treat and prevent dental caries may lead to large medical expenses for insurers, patients, and the public health safety net. The analysis of the NHAMCS by Wall and Nasseh (2013) supports this, finding that dental emergency room visits in the United States increased from 1.1 million in 2000 to 2.1 million in 2010, with a statistically significant
increase as a percent of total emergency room visits from 1.06% of total emergency room visits in 2000 to 1.65% in 2010 (Wall and Nasseh, 2013). The increase in dental emergency department visits was primarily accounted for by young adults between ages 21 to 34, who generally face the highest cost barriers to dental care out of any age group, but who may have health insurance (up to age 26) as a dependent on a parent’s insurance plan or may have an offer of employer-sponsored health insurance. Using the 2009 HCUP Nationwide Emergency Department Sample (NEDS), which is the largest all-payer emergency department database in the United States, Seu et al. (2012) finds that the major payers for hospitalized patients among those using the ED for dental conditions in 2009 were Medicaid, followed by private (health) insurance (Seu et al., 2012).

The use of emergency departments for dental conditions may be especially important with the recent private and public health insurance expansions through the Affordable Care Act. Chalmers et al. (2016) found that the rollout of the 2014 Medicaid expansion in Kentucky occurred simultaneously with a dramatic increase in the number of ED discharges for conditions related to dental or oral health - though ED discharges for all diagnoses among Medicaid adults doubled with the increase in Medicaid coverage, the number of discharges related to dental conditions nearly tripled. While the overall increase in overall ED visits was not unexpected based on the Oregon Health Insurance Experiment that found an increase in ED use, the dramatic increase among dental-related ED visits is novel. This may imply that when insurance expansions reach populations with higher risk of poor oral health, the pent-up demand for dental care may manifest in emergency room and outpatient visits that are ineffective at treating the underlying oral health condition - patients typically receive prescriptions to treat symptoms (such as pain, toothache, and infection), antibiotics, or analgesics (Chalmers et al., 2016).

Given the possible effect of dental care on decreasing medical expenditures, spillovers to the public health safety net (especially hospitals and state Medicaid programs) and to overall health expenditures, the stakeholders that may benefit most from increases in utilization of
effective dental prevention are states and health insurers. Given the research currently being generated on the linkage between dental and systemic (overall) health and the underlying costs, there have been some effort to internalize these externalities by some private insurers and some Medicare Shared Savings Program (MSSP) providers by integrating both medical and dental benefits (Avalere Health, 2016). This is because states and health insurers are best positioned to internalize the spillover effects of increasing preventive dental care on medical expenses. This suggests then a two-pronged strategy to redesign the payment and delivery of dental care through the incorporation of dental benefits into health plans for higher income cohorts and the public provision of some types of preventive dental procedures to the most vulnerable populations. I discuss private plan provision of preventive dental care in the following section.

5.2. Optimal Insurance

Optimal insurance theory may provide some insight into whether dental benefits should be included into health plans or not. Pauly and Held (1990) discuss the conditions under which full coverage of preventive services would take place given profit-maximizing insurers or payers, which are as follows: 1) at minimum, the preventive service should be cost-effective; 2) there should not already be a large proportion of people who would purchase the preventive service without insurance; 3) consumers should be responsive to price changes for the treatment (high elasticity of demand); and 4) coverage should affect treatment decisions. Hence, I discuss each of these components.

1. Are dental services cost-effective? Though there exists a robust evidence base for the clinical efficacy of preventive dental services such as fluoride, silver diamine fluoride, and sealants, comprehensive economic evaluations of caries prevention methods are modest in number and quality (Niederman et al., 2015), primarily indicating that prevention is cost-effective for specific populations and countries. The cost-effectiveness studies in dental prevention primarily suffer from inability to compare between multiple methods of prevention, lack of detail on cost, and the absence of economic outcomes (such as education, school
attendance, income, days missed at work, and overall quality of life) that may have an impact on the overall cost-effectiveness ratio (Tonmukayakul et al., 2015) and other related outcomes (such as number of emergency room admissions averted or primary care visits for dental-related conditions). Hence, the cost-effectiveness research in dental care is an open and developing area of research with room for improvement (Griffin and Jones, 2013).

The cost-effectiveness studies and clinical trials examining effectiveness of preventive dental services (or dental services in general) typically fail to relate how dental treatments affect overall systemic health. Though there has been much discussion of the linkage between oral health and systemic health (Li et al., 2000), whether the associations are causal is not yet clear. For instance, there is a correlation between periodontal disease and adverse pregnancy outcomes, heart disease, stroke, and diabetes, but causation has not been established (Pihlstrom et al., 2005). However, randomized controlled trials for periodontal therapy have shown intensive periodontal treatment to improve lipid profiles that influence cardiovascular risk, relative to standard periodontal therapy (D’Aiuto et al., 2006). Perhaps as a result of the lack of evidence demonstrating that systemic diseases are caused by oral infection, clinical trials and cost-effectiveness studies in dentistry do not typically model or test for changes in health status. This may have an important effect on the estimated cost-effectiveness of dental treatments - if there are indeed salient and measurable changes in health status due to improvements in oral health that come from increased use of preventive dental treatment, then dental treatments may be more likely to be cost-effective.

Additionally, routine dental examinations may be a way to detect whether a patient is at high risk for diseases such as oral cancer, diabetes, and heart disease even before their primary care visits (Koneru and Tanikonda, 2015; Wright et al., 2014; Strauss et al., 2015), but current structures of reimbursement in dental insurance do not reward dental providers for checking for propensity for non-oral disease. Studies examining the efficacy of early detection of diabetes in dental settings also noted that the lack of coordination between dental and medical providers can mean that early detection in dental clinics may not translate to
follow-up care with patients’ primary care physicians (Wright et al., 2014). However, given that an estimated 8.1 million people in the United States with diabetes are undiagnosed, and an additional 86 million with prediabetes are also undiagnosed, routine dental examinations may be a valuable tool to identify and treat prediabetics in order to halt disease progression and diagnose and manage existing diabetic patients (Strauss et al., 2015).

Hence, there are pathways through which preventive dental care and routine dental examinations may have a measurable and large impact on health, but they have not been fully examined. As a result, more work is needed to determine whether these dental interventions would be worth the benefit received by the patient in terms of patient health and other relevant economic outcomes. This is especially true for dental interventions targeted at adults - much of the work in establishing cost-effectiveness of treatments have been aimed at children.

However, some studies have demonstrated that programs (primarily targeted towards children) implementing preventive dental care may be cost-saving to payers such as Medicare and Medicaid. Griffin et al. (2016) systematically reviewed the literature and found that from a societal perspective, school sealant programs at schools attended by a large number of high-risk children were cost-saving (the comparison was to having no sealant programs) and also improved the quality of life for children through decreasing the probability of needing future fillings and suffering toothaches. Given that the material cost of silver diamine fluoride is a small fraction of that for sealants ($0.10 per dose and $3.00 per application on multiple teeth) and can be applied by dental assistants instead of the dentist with an estimated clinical efficacy equal to sealants, upcoming economic evaluations of randomized clinical trials examining silver diamine fluoride relative to other preventive methods may indeed find that silver diamine fluoride is cost-saving as well. Quality of life measures may be especially important in evaluating preventive interventions such as silver diamine fluoride among non-pediatric populations, because silver diamine fluoride may stain the tooth partially black in areas where there are active infections. Hence, providing sealants may be
not only cost-effective but cost-saving from the perspective of public payers, but additional work examining the cost-effectiveness of other procedures (such as silver diamine fluoride) incorporating non-oral health outcomes of interest (such as quality of life and medical expenditures) are needed. Furthermore, it remains unclear whether preventive treatments that are cost-saving from a societal perspective would be cost-saving or cost-effective for insurers, given that the decreased costs from restorative procedures and decreased medical costs may need to accrue over a longer period of time (over one year) for provision of a preventive treatment to be cost-effective. If insurers retain enrollees over a relatively long period of time (perhaps due to inertia), then it is more likely that providing some preventive dental services may be cost-effective.

2. Do people already purchase dental services without coverage? Suppose then that preventive dental treatments and routine examinations are cost-effective - do individuals choose to purchase them even without dental coverage? Individuals without dental coverage have the option to see a dentist by paying out-of-pocket and/or purchasing a pre-payment plan directly from the office. Because data on uninsured dental patients is difficult to obtain other than from practice-level data from individual dental offices or dental schools, the best source of data is then survey data asking about dental utilization over a large population. Based on the 2000-2012 data from the Medical Expenditure Panel Survey, Nasseh and Vujicic (2014) found that in 2012, only 35.4 percent of working-age adults visited the dentist, and that there was a steady decline in utilization among this group over the time period analyzed. Wall et al. (2012) used data from the National Health Interview Survey (NHIS) and found similarly that among non-elderly adults, "utilization has been falling steadily since 1997 [to 2010] among all but the wealthiest income group", which appeared to be related to decreases in private insurance coverage and increases in public coverage, where the majority of adult Medicaid programs do not provide adult dental benefits. This is in line with Chalmers et al. (2016) mentioned in the previous section, which found that an increase in Medicaid adult coverage in Kentucky led to an increase in emergency department discharges due to dental-related conditions. Hence, this suggests that utilization
of dental services is tied to dental coverage and that loss of dental coverage leads to an increase in pent-up demand for dental services, ultimately culminating in increases in the emergency department (and possibly other medical facilities, such as primary care clinics) for dental-related emergencies.

3. **Are consumers responsive to price changes for dental care?** Though the literature is again lacking in empirical tests, the price elasticity of demand for dental care has been suggested to be high, because dental issues are seldom emergencies and dental care can be delayed for some period of time without significant consequences of overall systemic health Sintonen and Linnosmaa (2000). The best evidence to date estimating the price elasticity of demand for dental services comes from the RAND Health Insurance Experiment, where individuals were randomized to plans with varying levels of cost-sharing that covered medical and dental services under the same plan. They find that there is some evidence that dental services are "significantly more responsive... to cost sharing during the first year of dental coverage than are other outpatient health services" but are not responsive in the long run to cost-sharing. However, this result has limited applicability in the current dental insurance setting - the insurance coverage provided through the RAND experiment included both medical and dental services, and took the traditional insurance structure instead of being structured like current dental benefits which are similar to pre-payment plans for routine services. Meyerhoefer et al. (2014) found that use of preventive and restorative dental services was insensitive to out-of-pocket price, but this was based on MEPS survey data with potentially endogenous variation in dental coverage status and with no information on dental coverage levels across individuals. Further research is necessitated to examine this question, which will support whether or not preventive dental care should be incorporated into health insurance plans.

4. **Would adding coverage for dental services increase utilization of (preventive and/or cost-effective) dental care and/or decrease use of restorative services?**

There is evidence that having dental coverage in its current structure is associated with a
higher probability of visiting the dentist and having any dental utilization, but how much of this effect is from self-selection into dental insurance or an underlying demand for dental services is unclear. However, Nasseh and Vujicic (2015) states that "[individuals] with private dental benefits [are] twice as likely to visit a dentist compared to [people] without any benefits" and that the decline in private dental coverage in the population has occurred simultaneously with a drop in dental care utilization especially among working-age adults.

Potential areas to test for a causal linkage between inclusion of dental coverage in medical plans and increased dental utilization are the embedded pediatric dental benefits in medical plans on the health insurance exchanges through the recent Affordable Care Act, and dental benefits in Medicare Advantage plans that are available as part of plans by default or as an optional supplemental benefit.

However, it is not clear that the current structure of dental benefits should be used in medical plans primarily because of the incentive to use restorative over preventive care generally from the current fee-for-service system. Excluding restorative treatment from benefits may be only a partial solution that ignores the demand for restorative treatments among individuals with pent-up demand for dental services and whose underlying severity necessitates some restorative treatments. Even if preventive treatments were to be reimbursed highly over restorative treatments, this may not be sufficient to account for the loss of future income from using preventive treatment, dental providers may refuse to participate, or public provision of preventive care through alternate methods of delivery may be more cost-effective.

Restructuring dental provider payments to be based on a bundled payment mechanism rather than on fee-for-service may be a solution to the problem of how to provide dental providers with the proper incentives for treatment. There are multiple barriers to this, mostly due to the outstanding questions of 1) how to define a cycle of care and measure changes in dental health, 2) how to define which preventive dental procedures are cost-effective and under what conditions to allow for treatment variability, and 3) how to measure
quality of care to encourage appropriate care. Because dentistry does not have "a tradition of formally reporting specific diagnoses or associating such diagnoses with specific services, especially through the claims process" (Dental Quality Alliance, 2016), there is currently no diagnoses in dental claims used to track patient outcomes within diagnosis groups nor to trace quality and appropriateness of the dental care provided to the patient. Instead, measures that are typically used in dentistry are process measures rather than outcome focused measurements (Dental Quality Alliance, 2016). To begin to bridge this gap, a set of dental diagnostic codes (SNO-DDS) was recently approved as a national standard and has been implemented in electronic dental record systems at several universities including New York University College of Dentistry, with more expected to adopt in the next few years (Manchir, 2016).

**Should Health Insurers Incorporate Dental Benefits?** Though there is a move towards establishing the linkages between medical and dental costs generally, there is yet more work to be done to establish whether most preventive dental procedures are cost-effective, and whether coverage of preventive dental procedures would influence patients’ and providers’ treatment choices. Additionally, the current structure of dental payment may not suffice for efficient delivery of preventive dental services, and changing the system of reimbursements to dentists to align with current clinical evidence would require an upheaval of current claim processing requirements for dental offices to implement dental diagnostic coding and the development and standardization of oral health outcome measures instead of process measures. Dentists would also need to be willing to participate in insurance plans implementing these changes, which is only likely to take place given either inclusion of dental benefits into essential health benefits, or if dental insurers are able to ensure patient volume in dental offices. More concerning, however, is that a shift towards preventive dental care and away from restorative care may necessarily decrease the future demand for dental services and would require a major shift in the practice decisions of dentists.
5.3. Conclusion

There is a general concern that while there may be societal welfare gains from increased provision of clinically effective preventive dental procedures, the current structure of dental insurance and reimbursements to dental providers and the practice patterns of dentists tends to incentivize restorative over preventive care. As a result, though public programs such as Medicaid and private health insurers may benefit from the decreases in medical expenditure and utilization from improved dental utilization among their relevant populations, there is still work to be done to establish the cost-effectiveness of many preventive dental treatments and the linkage between dental and medical costs to incentivize payers to overhaul the current structure of dental insurance. Additionally, an overhaul of current dental insurance structure would imply a major shift in how dentists practice and are trained to practice, which would need to involve reform of scope of practice acts and dental school training.
CHAPTER 6 : Conclusion

In this dissertation, I examine the supply-side effects of insurance expansions through the lens of models of provider behavior with demand inducement. Because the problems with provider agency that exist in medicine also exist in dental, and there exists substantial excess capacity within dental practices, a private insurance expansion provides an opportunity to test for whether demand inducement exists among dentists and whether insurance expansions are an available policy lever to decrease the amount of provider-initiated overutilization. Furthermore, Chapter 6 introduces the idea that the incentive to induce demand for dentists is exaggerated through the misalignment of provider reimbursement with the clinical benefit of dental treatments. Given that mispricing of procedures is an issue also in general health care markets, evaluating whether insurance expansions will exacerbate or limit the problems with provider incentives given suboptimal plan design is a salient topic that applies to the health care market more generally, and can be evaluated in the dental market.

In particular, the dental market is a setting in which the incentive to induce demand is exacerbated by the misalignment and opposition between provider financial incentives and the clinical efficacy of dental treatments. Though the majority of dental caries are seen to be preventable through improvement of dental hygiene habits, due to the nature of caries progression which is non-linear and fluctuates over time between remineralization and demineralization, providers generally are not reimbursed well or at all by insurance plans to assess risk for caries or improving dental hygiene habits of patients. Similarly, there exist a number of low-cost preventive dental procedures that can arrest or prevent the progression of cavities, such as silver diamine fluoride, sealants, and fluoride (Niederman et al., 2015, forthcoming), which are simple and quick to provide, that are either not reimbursed by dental plans or at very low levels. Because of the low reimbursement rates, coupled with the potential effect that providing effective preventive dental care would have on decreasing future profits due to decreased caries prevalence in the patient population, these procedures
(which are generally quick and cost very little to the dentist) tend to go underused.

A priori, the simple extension of the McGuire and Pauly (1991) model of provider behavior with demand inducement suggests that even when there is an incentive to induce demand for more intensive, restorative procedures, an increase in private dental insurance coverage may decrease the incentive to induce demand and lead to shifts away from restorative procedures towards preventive and/or routine procedures. Hence, rather than exacerbating the problem of provider-initiated overutilization of restorative care and under-utilization of preventive care, a private dental insurance expansion could provide at least a short run solution to improve provision of preventive dental care. Given the monetary and political costs of overhauling the entire dental system (dental insurance, provider payment, and provider practice patterns), increasing dental insurance coverage may be a more efficient way to decrease concerns about demand inducement in dentistry.

To support this, I discuss in depth the general structure of dental insurance reimbursement to providers and where there is potential to induce demand, as well as the negative welfare effects on patients from demand inducement. To underline that the issue with dental reimbursement structures is not easily resolved and leads to a general incentive to reduce use of clinically effective preventive care and increase use of restorative dental procedures, a discussion of why the current divide between dental and medical insurance leads to the mis-pricing of dental procedures, and why dental insurers have little to no incentive to improve provision of clinically effective preventive care among their enrollees. Given that cavities are preventable bacterial infections, but are prevalent to epidemic proportions and are currently the fifth most expensive disease to treat, the underuse of preventive dental care and subsequent overuse of restorative care can lead to negative externalities for the public health safety net (especially for hospitals and emergency rooms, which are ill-equipped to deal with dental emergencies and are not cost-effective sources of dental care relative to receiving care at dental offices), health insurers (through increased likelihood of associated diseases), and the workforce. I then consider whether there are alternate ways of structuring the payment
and delivery of dental care, specifically through inclusion of dental benefits as part of a health plan. Though there are yet-unanswered questions about the cost-effectiveness of different dental procedures across various populations, the linkages between oral and systemic health, and the resulting linkages between oral health expenditures and medical expenditures, none of the answers thus far suggest that dental procedures should not be included as part of preventive benefits in health plans.

However, given the mispricing of procedures within current dental benefit structures, I then seek to evaluate whether increases in enrollment in dental benefits as currently structured, such as through an insurance mandate or insurance expansion, would disincentivize high intensity, restorative procedures in favor of preventive and routine procedures. The answer to this question may then inform health insurers as to what would occur if they incorporated dental benefits into health plans with the current structure of reimbursement for dental providers. If the decreases in demand inducement are substantive given a "large enough" exogenous increase in demand for dental services, then increasing dental coverage regardless of its suboptimal payment structure (from a societal perspective and perhaps from a health insurer’s perspective) may be a feasible short run solution to shift dental practices away from restorative procedures towards more routine, preventive procedures. This is in contrast to overhauling and innovating new dental payment structures, or directly altering the way dentists practice or are trained.

Though the analysis finds that a unexpected increase in market demand for dental care from an insurance expansion leads to increases in office workloads, which then yield mild substitution away from high intensity cavity procedures, the substitution is towards routine procedures that are reimbursed by dental plans generally at 100% and with little to no preventive benefit to patients (in the case of diagnostic imaging procedures. This does not necessarily apply to cleanings, though there is currently no robust evidence on whether cleanings do or do not decrease the likelihood of cavities). As a result, though the decreases in the high intensity cavity procedures found in the analysis are almost unambiguously
welfare improving for patients, given the clinical background discussed in Chapter 2, the decreases may not be substantive enough to justify the increase in low-value treatments that are quick for dental providers to administer through dental hygienists. Hence, the results are mixed - though the analysis yields evidence pointing towards the existence of demand inducement among dental providers, it is unlikely that a dental insurance expansion or a dental coverage mandate would lead to increases in clinically-effective preventive care. Instead, an increase in coverage for dental benefits as currently structured would likely yield a decrease in capacity-intensive, high intensity low value treatment to low intensity, low value treatments that are not capacity intensive. As a result, more work is yet to be done on how to increase provision and utilization of preventive dental care, especially for adults and for those with insurance coverage.

Because catastrophic dental costs or catastrophic medical costs resulting from insufficient utilization of clinically effective preventive care do not fall upon the dental insurer, dental insurers are not incentivized to decrease the incentives for demand inducement nor to provide incentives for dental providers to increase utilization of clinically effective preventive care. I then discuss the policy levers available for addressing the misalignment of clinical efficacy and provider reimbursement, using the theory of optimal insurance and optimal coverage of preventive care. However, given the substantial costs to reforming delivery and payment of dental care, many of the suggested solutions are not implementable in the short run.

Though the theoretical literature on provider behavior and inducement suggests that an insurance expansion may provide a short run solution to decrease the overall incentive to induce demand in dental practices, I find that the substitution away from intensive procedures towards routine procedures in the context of reimbursement systems that are heavily flawed and that give ample incentive to induce demand for intensive services suggest that insurance expansions may decrease (at least in the short-run) the incentive to induce demand and to increase utilization of lower intensity procedures. However, the increase in
utilization among lower intensity, routine, and/or preventive services is limited to treatments that are reimbursed well by the insurer. For instance, treatments that have been clinically shown to be effective in preventing cavities and that have been shown to be cost-effective or cost-saving under certain scenarios, such as sealants, do not see an increase in utilization. This may be because of the decrease in future income that results from using highly effective preventive care.

As a result, the analyses suggest that though insurance expansions do not exacerbate incentives to induce demand via imperfect reimbursement mechanisms to providers, they do not solve the issues of low utilization of clinically effective preventive care. However, insurance expansions may bridge the gap between the status quo - not reforming and not decreasing the amount of demand inducement by providers - and completely reforming the payment and delivery system in dental markets. This is because a sufficiently large enough dental insurance expansion may shift practice patterns towards lower intensity treatments, and reconcile the differences between the current system of dental care delivery focused primarily upon restorative care and a system focused upon delivery of preventive care that may be preferred by patients, medical insurers, and policymakers. A gradual shift away from restorative care-based dental practice patterns could lead to a shift to how dentists are trained to practice, thus clearing the way for reform of scope of practice acts and dental school training.
Appendix

A.1. Full Theoretical Model

I extend the McGuire and Pauly (1991) model to incorporate capacity constraints, moral hazard among the newly insured, and distinguish between newly insured and continuously insured patients. To do this, I follow the general framework of McGuire and Pauly (1991), where providers have utility over total income $Y$ and disutility from total inducement $I$. We assume that utility is separable in income and inducement. The objective function is then given by the following:

$$U(Y, I) = U(Y) + U(I)$$

Total inducement $I$ is made up of the inducement levels per person for each service $j$, called $i_j$. The inducement level with the out-of-pocket price of treatment $p_j$ affects the quantity response $x_j$, which is a function that gives the amount or intensity of each service type supplied to the patient. The higher the inducement level, the higher the quantity or intensity of the service. However, $x_j$ is also affected by the out-of-pocket price of treatment $p_j$. The higher the out-of-pocket price of treatment $p_j$, the more inducement effort required to achieve a given level of quantity or intensity. This results in $x_j = x_j(i_j, p_j)$, where $\frac{dx_j}{di_j} > 0, \frac{dx_j}{dp_j} < 0, \frac{d^2x_j}{di_jdp_j} < 0$. This captures the idea that when patients do not face the full price of treatment (especially for routine procedures, such as cleansings and X-rays) when they become insured, patients will demand more services so that less inducement effort is needed to achieve each level of quantity or intensity. Each service receives a margin per unit that encapsulates both the total reimbursement received by the provider for providing
the service, net of material, labor (for example, the labor supplied by the dental hygienist in the practice), and time costs. The more intense or the more quantity that is supplied of each service per patient, the higher the profit from that service.

I separate patients into two different groups in the practice, the continuously insured and the newly insured. There are four potential groups of patients in the practice: 1) those who were previously and continue to be insured and seeing the dentist, 2) those who are newly insured and were not seeing the dentist previously, 3) those who are newly insured and were seeing the dentist out-of-pocket previously, and 4) those who are seeing the dentist out-of-pocket. Of these groups, the two that can be identified in the data are groups (1) and (2), the continuously insured and the newly insured. Because the effect of the insurance expansion used in this paper primarily increases insurance rates among those previously not seeing the dentist out-of-pocket (discussed later in Section V on data and measurement), I abstract away from groups (3) and (4), those who were seeing the dentist out-of-pocket without insurance at some point in time. The number of continuously insured patients is given by \( N_1 \) and the number of newly insured patients who were not previously seeing the dentist is given by \( N_2 \). Hence, the total inducement effort in the practice is given by

\[
I = N_1 \sum_{j} i_{1j} + N_2 \sum_{j} i_{2j}
\]

Similarly, the income in the practice is given by

\[
Y = N_1 \sum_{j} m_j x_{1j}(i_{1j}, p_{1j}) + N_2 \sum_{j} m_j x_{2j}(i_{2j}, p_{2j})
\]

where \( p_{1j} \) and \( p_{2j} \) capture the difference in out-of-pocket price for continuously insured and newly insured patients. Here, \( p_{1j} \) and \( p_{2j} \) are equal given enrollment in insurance, but when
group 2 newly receives insurance, they also experience a shock to their out-of-pocket price for treatment, which previously was prohibitively high (so that they were previously not seeing the dentist without insurance) and declines after insurance receipt. The change in $p_{2j}$ captures the idea that patients may increase their consumption of dental services and be less resistant to inducement when the out-of-pocket price of services declines, especially for cleanings and X-rays, upon becoming insured in a dental plan.

To incorporate the capacity level of the practice $K$, which can represent the combination of the provider’s labor supply along with the physical capacity of the practice (i.e. the number of chairs available), I require that the total intensity and quantity of services required does not exceed $K$. Each service takes up $t_j$ units of the office’s capacity, and the higher the intensity or quantity provided of the service, the more capacity is used ($t_j x_j$). The shadow cost of expanding the practice capacity $K$ is given by $\lambda$. The capacity constraint as a result is

$$K - N_1 \sum_j t_{1j} x_{1j}(i_{1j}, p_{1j}) - N_2 \sum_j t_{2j} x_{2j}(i_{2j}, p_{2j}) \geq 0$$

The resulting optimization problem is then the following:

$$\max_{i_{1j}, i_{2j}} U(Y, I) = U(Y) + U(I)$$

s.t. $K - N_1 \sum_j t_{1j} x_{1j}(i_{1j}, p_{1j}) - N_2 \sum_j t_{2j} x_{2j}(i_{2j}, p_{2j}) \geq 0$

with $Y = N_1 \sum_j m_j x_{1j}(i_{1j}, p_{1j}) + N_2 \sum_j m_j x_{2j}(i_{2j}, p_{2j})$

$I = N_1 \sum_j i_{1j} + N_2 \sum_j i_{2j}$

Using the Lagrangian method and placing $\lambda$ as the Lagrangian multiplier on the capacity constraint, I obtain the following optimality condition for each group and service combina-
tion (suppressing the group and service identifiers for simplified notation):

\[ m_x = \frac{-U_I + \lambda t x_i}{U_Y} \]

where \( U_Y \) and \( U_I \) are respectively the marginal utility from total income and marginal disutility from total inducement, and \( x_i \) is the marginal increase in the quantity response from the inducement level per service per patient. The predictions generated from this optimality condition are the following:

**Prediction 1:** An increase in office size leads to downward pressure on inducement levels per service per patient.

As in the McGuire and Pauly (1991) model, an increase in \( N \) leads to an increase in marginal disutility from total inducement and a decrease in marginal utility from total income, holding fixed levels of inducement. To bring the optimality condition back to equality, there must be a decrease in the amount of inducement per service. In addition, an increase in \( N \) may also cause the capacity constraint to become binding so that the shadow cost of expanding capacity becomes nonzero (\( \lambda > 0 \)). A nonzero shadow cost puts additional downward pressure on inducement levels per service per patient, and this downward pressure is stronger for services that take up more capacity in the practice (\( t \) is higher). This leads to:

**Prediction 2:** An increase in office size that makes the capacity constraint bind, holding fixed levels of inducement per service per patient, leads to decreased inducement per service per patient, with stronger results for services that take up more capacity in the practice.

We also have

**Prediction 3:** A decrease in (due to the gain in insurance coverage upon the
newly insured group) leads to an increase in the quantity of services for the newly insured.

Because Predictions 1 and 2 imply a decline in the level of inducement per service per patient, leading to a decline in quantity for more intensive services, while Prediction 3 implies an increase in quantity for all services among the newly insured, there is an ambiguous prediction for the quantity of services provided per newly insured patient. To avoid ambiguous predictions, I focus attention on the continually insured in the practices who are not experiencing abrupt changes in plan design. However, if the capacity constraint becomes binding and the effect of capacity especially for more time- and capacity-intensive procedures (that generally tend to be more intensive services in dentistry) dominates the moral hazard effect for the newly insured, it may be possible to detect a stronger decline in the quantity of services provided per newly insured patient for more intensive services relative to less intensive services (such as cleanings and X-rays).

**Hypothesis 1:** An increase in $N_2$ will lead to a decrease in inducement for the continuously insured.

**Hypothesis 2:** When capacity constraints become binding, an increase in $N_2$ will lead to stronger decreases in inducement for more capacity-intensive services among the continuously insured.

**Corollary:** Hypothesis 2 may hold for the newly insured if the capacity effect dominates the moral hazard effect for the newly insured.

Overall, the model implies that there may be a change in the general equilibrium of the quantity and quality of services provided across all patients, and thus implies spillovers onto continuously insured patients.


A. Frakt. You probably don’t need dental x-rays every year, July 2016.


R. S. King. A closer look at teeth may mean more fillings. November 2011.


K. Nasseh and M. Vujicic. Dental benefits coverage rates increased for children and young


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C. Saint Louis. Feeling guilty about not flossing? maybe there’s no need.


