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Elena Falcettoni

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Dedication

To my mother, Nevia Turco, and my father, Mario Falcettoni: my education and my achievements are only a fruit of your love and sacrifice.

Every time I took a step, you were the floor holding me up; every time I caught a breath, you were the oxygen giving me life; every time I fell, you were the hand catching me.

A mia mamma, Nevia Turco, e a mio papà, Mario Falcettoni: la mia educazione e i miei traguardi sono solo il frutto del vostro amore e dei vostri sacrifici.

Ad ogni passo, siete stati il pavimento che mi sosteneva; ad ogni respiro, stiete stati l'ossigeno che mi ravvivava; ad ogni caduta, siete stati la mano che mi rialzava.

Abstract

This dissertation studies how physicians respond to incentives in terms of: their treatment choice, their geographical distribution in the United States, and their effect on health outcomes. To address this, I exploit micro-data from Medicare at a physician-procedure level. I then supplement this dataset with novel, granular data collected from physicians' directories that follow physicians from their choice of medical school onward. Chapter 1 introduces the topic and presents an overview of the questions analyzed and results obtained throughout the dissertation. Chapter 2 analyzes primary care physicians' response to fee-for-service pricing along the urban/rural divide. In particular, it first documents that primary care physicians provide more (remunerative) specialty procedures in less urban areas, where specialists are fewer; secondly, it analyzes how primary care physicians switch to the more remunerative procedures when their fees are increased. Chapter 3 develops a model of physicians' location choices and uses it to explore the impact of policy changes (loan forgiveness and salary incentives) on the geographical distribution of physicians. Chapter 4 provides evidence on the impact of the physician workforce on health outcomes by exploiting the policy-set fees and the micro-data availability.

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Chapter 1

Introduction

There is a large literature concerning how physicians respond to incentives. In particular, there is a large body of work concerning their response to fee-for-service payment systems (Clemens and Gottlieb 2014, Acemoglu and Finkelstein 2008, Finkelstein 2007, American Hospital Association 2008, Lori 2009, just to mention a few) and their response to policies aimed at creating incentives to affect the geographical distribution of physicians (namely, loan forgiveness and salary incentives). While many papers focus on the effect that such incentives have on particular procedures (see, for example, Gruber & Owings 1994, Grant 2009, Shrank 2005, Jacobson 2006), there is a need to shed some light on the mechanisms through which incentives arise and their effect on physicians' choices and, ultimately, on the affected American population.

To analyze these topics, I present three chapters in this thesis that address physicians' responses to different types of incentives and their effect on the choice of treatment, the geographical distribution of physicians, and their impact on health outcomes. To be able to fully understand the margins that impact these choices, all of my research has three points in common across all chapters. First, my thesis keeps in mind the great urban/rural divide in health care access in the United States. In particular, since about 25% of the American population lives in medically underserved areas where fewer than 10% of physicians operate, the urban and rural parts of the country would be impacted differently by different health care reforms. This thesis documents how physicians' behavior by specialty group differs according to the urbanity of the area and exploits these geographical differences in its identification strategy. Second, my thesis shows that the two main specialty groups, namely primary care and specialty care, behave quite differently from one another, and the differences between the two create interesting margins. In particular, my research shows that primary care physicians behave like specialists in more rural areas, which generates an interesting financial margin in a fee-for-service payment system. These differences need to be accounted for when modeling physicians' geographical location choice as the mix of procedures carried out by physicians in different places is highly dependent on both the urbanity of the area and the specialty of the physicians themselves. Finally, these chapters rely heavily on big micro data. The first dataset comes from Medicare and reports all fee-for-service reimbursements received by physicians for Medicare Part B. These micro data shed light on the mix of procedures carried out and the response of physicians to changes in financial incentives dependent on the procedures themselves. This dataset is then augmented by micro data that I collected from physician directories containing information on physicians' education and training from medical school onward. This information is then linked to public rankings to approximate quality rankings of physicians.

The second chapter provides evidence for a supply-induced demand mechanism that is compatible with the increasing trend in healthcare spending in the US. Using data on the Medicare universe of physicians (therefore excluding hospitals) and the BLP (1995) algorithm, controlling for demographic and regional variation, I analyze physicians' response to financial incentives. There are many margins through which financial incentives can arise. The key margin this chapter analyzes is the urbanity level of the area where the doctor practices. In particular, I focus on primary care physicians' ability to take on more specialized, lucrative treatments along the urbanity margin. Primary care physicians see patients first and face the decision of whether or not to recommend a patient to a specialist.

The reimbursement rate, therefore, generates a financial incentive which affects the margin of the primary care doctor passing the procedure along to a specialist versus carrying it out him/herself. Reduced-form results suggest that primary care doctors react strongly to increases in the reimbursement units. An increase of one unit in the reimbursement factor (equal to a salary increase shy of $36) leads to 57 more services provided by primary care in the more remunerative procedure and a 45% higher chance that they will increase the number of specialist services provided. Structurally, I find that primary care physicians are able to take on more specialist services in less urban areas, where they gain higher market shares due to the lower number of specialists in close proximity. In particular, the increase in the weight of the primary care physicians' financial interests in the consumer utility ranges between 7-15% compared to physicians in large metropolitan areas, at the expense of specialists. Small metropolitan areas (population>50,000) and very rural areas (population<10,000) are the most affected. This chapter therefore provides a key insight to the issue of overutilization by showing that a change in financial incentives also leads to a reallocation of procedures among the different providers carrying them out. Considering the primary care physicians' increase in specialty procedures caused by the increased financial incentives as overutilization would overlook the fact that this increase comes at the expense of specialists, as analyzed in this chapter. Therefore, this chapter provides evidence that it is key to consider two complementing effects caused by fee-for-service: a reallocation of the procedures carried out from specialists to primary care physicians for any given total number of procedures, as shown here, and the increase in the number of total procedures carried out overall without an apparent increase in patients' health issues, the latter of which is not analyzed in this thesis.

The third chapter addresses a long-standing challenge in the US health care system, which is the provision of medical services to rural areas, where 25% of the population live, but only fewer than 10% of physicians operate. This chapter develops a model of physicians' location choices and uses it to explore the impact of policy changes (loan forgiveness and salary incentives) on the geographical distribution of physicians. I build a structural spatial equilibrium model in which physicians are heterogeneous along their specialty, demographics, and skill. Identification of the parameters of interest is challenged by the possible correlation between unobserved characteristics of location and wages, as offered wages are higher where amenities are fewer. To overcome this issue, I collect micro-level data from physicians' directories on doctors' medical school, residency, and first job choices. This wealth of information and structural methods of demand à la Berry, Levinsohn, and Pakes (1995) allow me to back up the unobserved characteristics and be exactly identified. I allow individuals the preference to remain close to their residency location and let each medical resident's job choice set depend on his or her skill. I find that all residents display a strong retention preference and that primary care physicians in particular are 3.5 times more likely to pick a job within the same state and 4 times more likely to pick a job within the same area as their residency. I then use the model to analyze the performance of current policies targeted at bringing physicians to rural areas. I find that 0.5% more primary care residents and 1.3% more specialists have picked rural areas due to loan forgiveness alone. Monetary incentives in the form of bonus payments averaging $7,500 are responsible for a further 0.2% increase in primary care physicians and 0.1% increase in specialists. By retargeting the spending currently used for loan forgiveness to higher salary incentives for rural employment, I find that almost 6 times more primary care physicians would pick rural areas compared to the effect of loan forgiveness. Since primary care physicians are the main physician category that currently provides medical care to rural areas, and since they do not need a particular infrastructure to do so, these results suggest that policymakers should retarget spending from loan forgiveness to salary incentives and that offering salary incentives to primary care physicians only would be even more effective.

The average quality of the physicians attracted under these higher salary incentives is also better compared to loan forgiveness. Another possible policy intervention suggested by the high persistence in physicians' location choices is the use of these monetary incentives to create rural residencies. Since the residency choice is not directly modeled in this chapter, this question is outside the scope of this thesis but will be addressed in future work.

The final chapter links the physician workforce with its effect on the population's health outcomes. The effect of the physician workforce on health outcomes of the American population is a key, yet still poorly understood relationship. Policy proposals tend to link better health outcomes with a larger physician workforce, but there is no study that shows a causal relationship between the physician workforce and the health outcomes of the affected population. This chapter seeks to partially fill this gap by providing a first step toward an identification strategy for the effect of physicians on health, utilizing both an instrumental variable strategy with exogenous policy shocks as well as detailed micro-data on procedure revenue. The link between better health outcomes and a larger physician workforce mainly rely on two facts. First, mortality is higher in rural than in urban areas, across and within all age groups and across and within all causes of deaths. Second, physicians are concentrated in cities, and this is true within and across specialty groups. These facts clearly illustrate that cities attract both more physicians and healthier people, but whether these two facts are causally related is not as obvious. There are many variables, in fact, that are correlated with both the physician concentration and health outcomes which will bias the coefficient on the physician workforce upward with any regression analysis that does not take this endogeneity into consideration. This chapter implements an instrumental-variable approach that exploits the great variation in the procedures carried out across and within areas joint with the changes in the policy-set fees for such procedures for both primary care physicians and specialists to instrument for the physician concentration. To understand the impact of physicians on the mortality rate, the chapter also utilizes an age-race-gender adjusted mortality rate to account for the geographical differences in age, gender, and race across the population, as not doing so would lead to bias in the coefficients. Results from the IV estimation indicate that an increase in one more physician per 10,000 saves, on average, 4.5 lives based on an average of 4,484 deaths per 100,000 residents, which is about 1/10 of the effect usually reported by cross-sectional analyses. The results therefore indicate that cross-sectional analyses display a large upward bias, which is typical of linear regression analyses where endogeneity is present.

Chapter 2

The Consequences of Medicare Pricing: An Explanation of Treatment Choice

2.1 Introduction

The increase in national health expenditure for the United States, which accounts for 17.8% of the US GDP (Centers for Medicare & Medicaid Services, 2015), has captured the interest of academics and non-academics alike for decades. On average, half of physicians' income is composed of fee-for-service payments. Medicare, the public health insurance for the elderly, accounts for 20% of total health spending and utilizes a fee-for-service reimbursement scheme for the original Medicare Part B. Critics and the media have contended that fee-for-service generates financial incentives for physicians. For example, case studies have found supporting evidence that fee-for-service leads to overutilization of procedures without an underlying reason to be found in patient health conditions (see, i.a., Levin & Rao 2008). Fee-for-service reimbursements have been increasingly higher for specialty procedures than for typically primary care procedures. Since the reimbursement does not depend on who carries out the procedure, but only on the procedure itself, and specialty procedures are more highly priced than typical primary care procedures, this payment system generates financial incentives for primary care physicians to substitute to more specialized, remunerative procedures whenever possible.

There are many margins through which financial incentives can arise. The key margin this chapter analyzes is the urbanity level of the area where the doctor practices. First, the chapter documents the novel fact that primary care physicians are able to take up a higher share of specialty (more remunerative) procedures, the more rural the area, where fewer specialists practice. Second, this chapter studies how the financial incentives generated by fee-for-service affect the demand for specialized procedures due to doctors inducing demand for the more remunerative, specialized procedures. In particular, primary care physicians see patients first and face the decision of whether or not to recommend a patient to a specialist. The reimbursement rate, therefore, generates a financial incentive which affects the margin of the primary care doctor passing the procedure along to a specialist versus carrying it out him/herself.

This chapter provides a key insight to the issue of overutilization by showing that a change in financial incentives also leads to a reallocation of procedures among the different providers carrying them out. Considering the primary care physicians' increase in specialty procedures caused by the increased financial incentives as overutilization would overlook the fact that this increase comes at the expense of specialists, as analyzed in this chapter. Therefore, this chapter provides evidence that it is key to consider two complementing effects caused by fee-for-service: a reallocation of the procedures carried out from specialists to primary care physicians for any given total number of procedures, as shown here, and the increase in the number of total procedures carried out overall without an apparent increase in patients' health issues, the latter of which is not analyzed in this chapter.

This chapter utilizes micro-data from Medicare for all its estimations. It has been largely documented that the Medicare reimbursement system largely influences the payment system of about 80% of American doctors (Clemens & Gottlieb 2017). If this is indeed the case, the effect found of this chapter is generalizable to fee-for-service payment schemes outside of Medicare.

First, this chapter shows a novel data finding that primary care physicians take on more specialty procedures, the more rural the area. To analyze this fact, I create a specialization index of procedures using the data on all procedures carried out by all physicians participating in Medicare Part B from 2012 to 2015. I then classify procedures based on the type of physicians who would usually carry them out. Finally, I analyze which physicians provide procedures which are classified as specialty procedures along the urbanity index.

Second, I run reduced-form tests to provide empirical evidence that the number of specialty procedures carried out by primary care physicians and their probability to carry them out is affected by changes in the reimbursement amount.

Finally, I turn my attention to the estimation of the demand curve. I set up a structural random coefficients model of demand for healthcare with a supply-induced mechanism in which primary care physicians enter the consumer's utility through the reimbursement fees set by policy. I estimate this effect using Medicare (Part B) data on physicians reimbursements from 2012 through 2015, the demographic variation present in the data, and the policy-set reimbursement fees. Two challenges are faced. First, in order to identify the impact of reimbursement, it is crucial to control for demographic and region-wide differences. Its identification relies on consumers not reacting to the amount of reimbursement the doctor receives, and this is how the micro-data on Medicare becomes key in the estimation. Since all patients considered are insured by Medicare for the procedures analyzed and do not have to pay for the entirety of the bill, and since the reimbursement units are based on the procedure carried out and not on the physician him/herself, patients would not internalize the reimbursement units in their demand system outside of the physician's influence on their decision. Second, similar to the estimation of demand curves in other industries, the endogeneity of the price paid by patients could lead to a biased estimate of the price coefficient. I observe the amount billed by doctors and the amount reimbursed by Medicare, from which I can impute the price faced by patients. Similarly to a higher-quality product in another industry, a provider could be picked more often despite having higher rates (translating into higher co-pays) due to friendliness, word-of-mouth reputation, or personal attachments. This would bias the price coefficient upward, indicating a lower elasticity of patients to prices, when instead the choice of the higher-rate physician would be due to factors that are unobserved by the econometrician. To tackle this issue, I use instrumental variables which represent input costs. These costs would increase a physician's pricing menu but not be observed or considered by patients, which is the identifying assumption necessary for the instruments to work. The instruments I use are malpractice insurance reimbursement fees as a proxy for malpractice insurance and cost-of-living adjustments for work, practice expenses, and malpractice insurance to proxy for regional variation in input costs. In the specifications that account for additional heterogeneity, I supplement these instruments with functions of the same instruments, as common in the literature: the interaction term of the work geographical adjustment factor with the practice expense geographical adjustment factor, the square of the work geographical adjustment factor, and the square of malpractice reimbursement units.

The results from this chapter show that primary care physicians indeed increase their share in specialty procedures more, the more lucrative they become, and are able to do so more, the more rural the area they practice in. The analysis of this chapter focuses on treatments carried out by specialists 60-80% of the time (and by primary care the remaining 20-40% of the times). Robustness checks, available in the online appendix, show that the results are robust independently of the range chosen, but their effect is stronger for tighter ranges. From the reduced-form results, I find that an increase in one unit of reimbursement for a given procedure, equal to an increase in reimbursement of about $36, leads to 57 more services carried out in that procedure and over a 45% higher probability of primary care physicians providing a higher number of the more lucrative procedure. Structurally, I find that the same $36 reimbursement increase for a given procedure leads to an increase in the primary care physician share in that specialty procedure by 7-15% more in less urban areas compared to their most urban counterparts, at the expense of specialists. I find that small metropolitan areas (with a population between 50,000 and 250,000 people) and very rural areas (with a population smaller than 10,000 people) are the most affected.

The rest of the chapter is structured in the following way: Section 2.2 reviews the existing literature. Section 2.3 introduces the data used in the chapter. Section 2.4 introduces the model. Section 2.5 provides the Reader with some introductory data analysis. Section 2.6 discusses the empirical evidence and reduced-form results. Section 2.7 presents the structural results and discusses the key parameters. Section 2.8 concludes and discusses future research.

2.2 Literature

This chapter primarily contributes to the strand of health economics literature discussing how physicians respond to financial incentives. Papers and articles have documented an increase in the demand for health goods coming from consumers and an increase in defensive medicine, i.e., doctors' decision to request treatments and procedures out of fear of being sued. Nevertheless, defensive medicine has been shown to only account for 0.46% of health spending (Anderson et al. 2005). Consumers, on the other hand, might indeed enjoy a higher consumption of health goods, but it would be puzzling if the entirety of spending was a direct effect of consumer preferences. First, it would be difficult to imagine that US consumers, who face higher co-pays than Europeans, were so intrinsically different in their preferences that their utility maximization would lead to higher consumption of more expensive health goods without any visible health effects. Second and most importantly, this would mean that US consumers switched their preferences quite dramatically, since this unbounded increase in health spending is quite recent. The other main school of thought suggests that the increase in medical spending can be explained by the rise in income since medical spending is a luxury good (Hall and Jones 2007). However, the assumption that medical spending is a luxury good is inconsistent with micro estimates showing that the income elasticity of medical spending is about 0.7 (Acemoglu et al. 2013).

A recent paper that addresses the incentives generated by fee-for-service is Clemens and Gottlieb (2014). Their analysis uses a 1997 change in Medicare geographical areas and focuses on two main procedures: MRIs and procedures for cardiac patients, such as cataract surgeries. They find that a 2% increase in payment rates leads to a 3% increase in care provision and that elective procedures respond more strongly than non-discretionary services. This chapter complements their analysis along several dimensions. Firstly, it is able to make more general statements on the reimbursement effect on treatment, without focusing on few case studies, but utilizing both the annual changes in reimbursement rates and the differences in the urbanity of the areas. Secondly, it documents and analyzes how primary care physicians specifically are able to increase the procedures they provide according not only to the reimbursement level, but to the urbanity level of the area where they practice, leading to a reallocation of specialty procedures from specialists to primary care physicians.

Finally, the use of a structural approach to analyze this issue modeling a supply-distorted demand system is novel on its own.

An extensive branch of literature has been written analyzing, from a reduced-form perspective, physicians' response to financial incentives in a hospital setting (i.a. Acemoglu and Finkelstein 2008, Finkelstein 2007, American Hospital Association 2008) and in a managed care setting (i.a. Lori 2009). However, the analysis of physicians' responses in their own practices seems to have been overlooked, even though the level and growth of healthcare spending for physicians is not negligible, as shown in Figure 2.1.

There are also different papers analyzing physicians' response to financial incentives

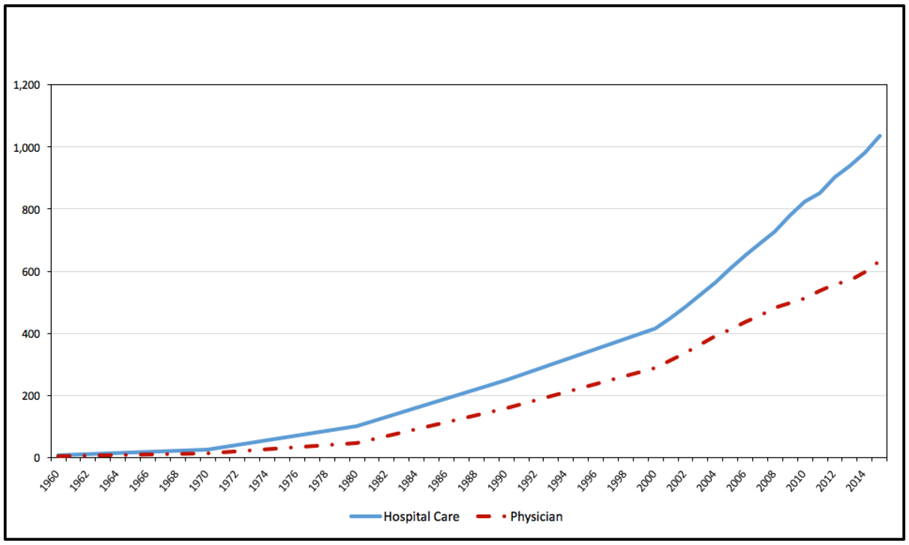


Figure 2.1: Aggregate Health Expenditure by Type of Care, $Bn

Notes: This figure shows the level of aggregate health spending differentiating between hospital care and physician-only care. Source: CMS.

for particular procedures (see, i.a., Gruber & Owings 1994, Grant 2009, Shrank 2005, Jacobson 2006). This chapter complements this strand of literature by setting up a structural model to physicians' behavior which is not confined to a few procedures as specific case studies, but generalizes this analysis by focusing on how the treatment picked is inherently tied to the profitability of the treatment itself and on the physician's location.

Papers have also been extensively written on the fee-for-service system's impact on health care costs and service overutilization (see, i.a. Ginsburg 2011, Hoangmai and Ginsburg 2007, Levin & Rao 2004). This chapter complements this literature by providing evidence that a change in financial incentives also leads to a reallocation in the providers carrying out the same procedures. Considering the primary care physicians' increase in specialty procedures caused by the increased financial incentives as overutilization would overlook the fact that this increase comes at the expense of specialists, as analyzed in this chapter. Therefore, this chapter provides evidence that it is key to consider two complementing effects caused by fee-for-service: a reallocation in the procedures carried out by each specialty for a given total number of procedures, and the increase in the number of total procedures carried out overall without an apparent increase in patients' health issues, the latter of which is not analyzed in this chapter.

Finally, the evidence of regional variations in Medicare spending has also been mentioned, not only in the literature, but also in the media (Gawande 2007 is probably the predominant example among many) and in the medical literature (see Fisher 2003 for example). This chapter makes an important contribution in this regard by providing a reason for such variation, i.e. primary care physicians' ability to respond to financial incentives in less urban areas more than their most urban counterparts.

Methodologically, this chapter bases itself mostly on Berry, Levinsohn, Pakes (1995, hereafter: BLP). The Medicare database does not actually provide data on the single patients, but it provides cumulative data on the patients seen by each doctor for each procedure carried out (some demographics, such as race, as well as many health variables, such as the number of people with cancer). This allows for a simulation of individuals that match the observed characteristic distributions in the data.

Readers who are interested in a deeper discussion on the institutional framework should refer to the Appendix Section A.8.

2.3 Data

The primary source of data for this chapter comes from the Centers for Medicare & Medicaid Services (CMS). The Physician and Other Supplier Public data provides information on services and procedures provided to Medicare beneficiaries by physicians. It contains information on utilization, actual Medicare reimbursement, and submitted charges. Each line of the dataset is indexed by a National Provider Identifier (NPI), which identifies each doctor in the dataset, by a Healthcare Common Procedure Coding System (HCPCS) code, which identifies every procedure carried out by each doctor, and by the place of service, indicating whether the procedures were carried out in a facility setting or not. The data is based on information from CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service program. The data are available for calendar years 2012 through 2015 and contain the universe of physicians taking part in Medicare Part B for the fee-for-service population. There are a little over 26.3 million observations in the dataset across over a million of physicians.

Despite the wealth of information on payment and utilization for Medicare Part B services, the dataset has a number of limitations. The data may not be representative of a physician's entire practice as it only includes information on Medicare fee-for-service beneficiaries. However, since Medicare influences the payment system of 80% of physicians (Clemens & Gottlieb 2017), this data allows for the analysis of physicians' behavior under this payment mechanism, which is then relevant for the greatest majority of doctors in the country. In addition, the data are not intended to indicate the quality of care provided and are not risk-adjusted to account for differences in underlying severity of disease of patient populations. To counter this, demographic data on patients' riskiness and incidence of diseases will be included in the estimation. Despite these limitations, some positive characteristics should be highlighted. First of all, the fact that all beneficiaries are covered by Medicare eliminates the issues related to the status of insurance of the beneficiaries. In particular, it allows me to abstract from other endogenous characteristics related to the insurance status of beneficiaries which would arise if a full dataset (not Medicare only) were used. Moreover, it also allows me to ignore the network effects of different insurance policies as well as their different payment plans. In practice, therefore, this dataset provides a more homogenous universe of insured individuals who receive different treatments according to the condition that they have.

As far as the illness and disease distribution is concerned, average beneficiary risk scores are provided on the "Medicare Physician and Other Supplier Aggregate Table" (i.e., one record per NPI) to provide information on the health status of the beneficiaries the providers serve for every year of interest together with the rate of incidence of a number of diseases and illnesses among the patients seen by each physician for every year. Therefore, this can account for the average health of the patients visited by each physician.

Finally, the Metropolitan Statistical Area definition follows the U.S. Census Bureau definition for Primary Metropolitan Statistical Areas (PMSA). The urban/rural classification also follows the U.S. Census Bureau definition according to the 2010 Census criteria. In particular, an urbanity index equal to: 1 indicates a large central metro, i.e. counties in MSAs with a population equal to or greater than 1 million that contain the entire population of the largest principal city of the MSA, or at least 250,000 inhabitants of any principal city of the MSA; 2 indicates a large fringe metro, i.e. counties in MSAs with a population equal to or greater than 1 million that do not qualify as large central metros; 3 indicates a medium metro, i.e. counties in MSAs with a population equal to or greater than 250,000 but strictly smaller than 1 million; 4 indicates a small metro, i.e. counties in MSAs with a population equal to or greater than 50,000 but strictly smaller than 250,000; 5 indicates a micropolitan area, i.e. counties in micropolitan statistical areas with a population equal to or greater than 10,000 but strictly smaller than 50,000; and 6 indicates a noncore area, i.e. the most rural classification, with a population that is strictly smaller than 10,000.

2.4 Model

This section models the ability of primary care physicians to gain an increasing share in specialty procedures along the urbanity index, at the expense of specialists. In particular, primary care physicians positively reach to increases in remuneration of a given procedure by increasing the number of times they carry that procedure out instead of referring it to specialists, and are able to do so more, the more rural the area. This section presents a structural random coefficients model with a supply-induced demand mechanism generated by the physician's utility for reimbursements entering the consumer's utility. The Appendix Section A.9 presents the model setup for the standard multinomial logit model of demand, which is a particular case of the model described here, where stochastic and demographic coefficients are not included. The main difference between the logit demand and the full structural model introduced here is that the marginal utilities of the product characteristics implied by the full model are different across consumers, and determined by the consumer characteristics. This breaks the independence of irrelevant alternatives (IIA) property typical of logit models, from which the simplified model in the Appendix would suffer.

I consider the choice of going to a specialist as the outside option. I assume that at this stage, the doctor has already decided what treatments to offer and the patients already know what treatment they need to receive. Therefore, consumers are faced with a product choice given by the type of doctor performing a relevant procedure for them.

Consumers' utility is composed of a mean utility and random stochastic coefficients dependent on demographic variables. I assume that the consumer maximizes a weighted sum of utilities, her own and her primary care doctor's, where the doctor's utility only enters the patient's utility in terms of the reimbursement obtained for the procedure carried out, i.e.

$$\begin{cases} u_{ijt} = & \max_j \left\{ \sum_{urban=1}^{6} (1-\gamma_{urban})\, u_{ijt}^{patient} + \mathbb{I}_{\text{PC}} \sum_{urban=1}^{6} \gamma_{urban} u_{jt}^{PC} \right\} \\ u_{jt}^{PC} = & RVU_{jt} \ \ \forall \text{ procedure codes} \\ \mathbb{I}_{\text{PC}} = & 1 \text{ if physician is in primary care (PC)} \end{cases} \tag{1}$$

$u_{ijt}^{patient}$ identifies the consumer/patient's utility while u_{jt}^{PC} identifies the doctor's utility. I define each market t as a Metropolitan Statistical Area (MSA)-year combination. Once the data is cleaned and markets with a single choice are excluded, I am left with 193 MSAs and a total of 764 markets (almost all MSAs are present for all 4 years of interest). Data are available for four consecutive years: 2012, 2013, 2014, 2015. Only primary care physicians are able to influence the consumers' utility, due to the fact that primary care physicians see the patient first and can choose to carry out the specialty procedure themselves instead of referring the patient to a specialist.[1] Therefore, $\mathbb{I}_{\text{PC}} = 0$ eliminates the supply-driven demand

[1]This assumption assumes away the possibility of patients referring themselves directly to a specialist. This would be the case in cities more than elsewhere, as specialists are more present in metro areas. This could partially explain the initial higher shares of more rural primary care physicians in specialty procedures compared to their urban counterparts. This initial differential would then be included in what I refer to as the "competition" coming from specialists in cities. In other words, primary care physicians in cities would initially carry out fewer EKGs, for example, both because more patients would go to cardiologists directly, and because out of those patients that would see a primary care physician first, a higher percentage would ask for a referral to a specialist even if offered an EKG by the primary care physician. However, the use of the time variation where the reimbursement increase is the mechanism that leads to a widening of this initial differential, with rural primary care physicians gaining a higher share of their urban counterparts. Therefore, even if patients could be part of the reason of why, at the beginning of the period, primary care physicians are able to do more specialty procedures in more rural areas, they would not choose whether or not to refer

mechanism. The extent to which physicians respond to the reimbursements depends on the urbanity (this is why γ_{urban} depends on the urbanity). The urbanity index is defined by the Census according to the population of an area and proximity to an MSA. It ranges from 1 to 6, where a higher value indicates a more rural area. In practice, I will report estimates for γ_{urban} for physicians in less urban areas compared to their most urban counterparts, i.e. physicians in large metropolitan areas with a population that is larger than one million and which fully contain an MSA. A product j is the combination of a procedure, indexed by its respective HCPCS billing code, and the provider group that carries it out, defined as: Primary care, Laboratory, Emergency medicine & general surgeons, and Specialists. As usual, the utility of the outside good (specialists) is normalized to zero.

Writing out the variables, the utility is equal to:

$$u_{ijt} = \sum_{urban=1}^{6} (1-\gamma_{urban}) \left(-\alpha_i p_{jt} + x_{jt}\beta_i + \xi_{jt} + \eta_{ijt}\right) + \mathbb{I}_{\text{PC}} \sum_{urban=1}^{6} \gamma_{urban} RVU_{jt} \quad (2)$$

which can be written as:

$$u_{ijt} = \begin{cases} \sum_{urban=1}^{6} (1-\gamma_{urban}) \left(\alpha p_{jt} + \beta x_{jt} + \xi_{jt}\right) & \text{patients' mean utility} \\ +\mathbb{I}_{\text{PC}} \sum_{urban=1}^{6} \gamma_{urban} RVU_{jt} & \text{physician's utility within mean utility} \\ +\left(-p_{jt}, x_{jt}\right) \sum_{urban=1}^{6} (1-\gamma_{urban}) (\Pi D_i + \Sigma \nu_i) & \text{stochastic coefficients} \\ +\varepsilon_{ijt} & \text{iid error term} \end{cases} \quad (3)$$

where $\left(p_{jt}, x_{jt}\right)$ are the product characteristics discussed below, ξ_{jt} are product-market unobservables, D_i is a 5x1 vector of consumer i's observable demographic characteristics

themselves based on changes in the reimbursement fees set by policy across time.

(age, gender, risk score proxying health issues, income in thousands, and square of the income in thousands), v_i is a 10x1 vector of the effect of consumer i's unobservable characteristics on α_i and β_i parameters; Π is a 10x5 matrix of how α_i and β_i parameters depend on the consumer observables, Σ is a 10x10 matrix of how those parameters depend on the unobservables; $\left(\nu_{i\alpha}, \nu_{i\beta}\right)$, $\left(\Pi_\alpha, \Pi_\beta\right)$, $\left(\Sigma_\alpha, \Sigma_\beta\right)$ split the vector into two parts. The values of D_i are picked from the main database as draws of 20 random individuals in each market. The values of ν_i are drawn from a multivariate normal distribution and are independent and identically distributed. The ε_{ijt} are drawn from Type 1 extreme value distribution and are independent and identically distributed across individuals, products, and markets.

I estimate four different specifications: a random coefficients model without the use of demographic variables, but only with a stochastic element on the reimbursement variable (in other words, the D_i vector is set to zero), a random coefficients model with demographic variables (the full version mentioned in this section), and a random coefficients model with and without demographics with the use of Chamberlain optimal instruments. The full specification of the model, a random coefficients model in which the random coefficients is estimated using the demographic variation present in the data, is the one presented here. The other specifications are all particular cases of this general one. Chamberlain optimal instruments are functions of the characteristics and instrumental variables, as commonly done in the literature.

I include ten product characteristics, equal to a constant and nine characteristics $\left(p_{jt}, x_{jt}\right)$ at a provider group-procedure-market level. These control for the average price to receive the procedure in that market carried out by that provider group, the relative value units earned for that procedure, a proxy for the level of specialization of the physician, the urbanity level, a proxy for the average level of education, and a proxy for competition. Price p_{jt} is derived from the total amount billed by the provider minus the amount reimbursed by

Medicare. The relative value units earned for that procedure, which are directly observed, capture the physician's ability to influence demand and are therefore the main variable of interest in this chapter. The average level of specialization of all procedures performed by physicians within each group measures the level of specialization of the procedures carried out by the average doctor in that market The average urbanity level of the doctors in that provider group and market, defined for each product, simply captures whether, on average, the procedure-provider group combination is more common in a more urban or rural setting. The average Medical Doctor (M.D.) index gives an index of whether the majority of doctors considered in that product-market combination have an M.D. degree or not. Given that each doctor can either be a M.D. (1) or not (0), this variable is between 0 and 1.[2] The proxy for competition is calculated as the average number of doctors in own and other provider groups in the same zip code as each doctor. Therefore, four variables proxy competition: the average number of primary care physicians, specialists, emergency medicine doctors, and laboratories in close proximity to each doctor considered. A higher number indicates a higher competition in that product-market combination.

As usually done in the literature, the utility can be simplified by calling the mean utilities δ's, for the patients and for the primary care physician respectively, a stochastic coefficient component μ, and the random error:

$$u_{ijt} = \delta_{jt}^{patient} + \mathbb{I}_{\mathrm{PC}}\delta_{jt}^{PC} + \sum_{urban=1}^{6} (1 - \gamma_{urban})\,\mu_{ijt} + \varepsilon_{ijt} \tag{4}$$

[2]The other type of degree that physicians can hold is a D.O. degree, which categorizes them as osteopathic physicians. Physicians with a D.O. are licensed in all 50 states to practice medicine and surgery, as well to prescribe medications. Anecdotal evidence seems to suggest that patients often display a preference for M.D. doctors, who they consider better qualified. This variable controls for this.

The market share of product j for consumer of type i in market t is then equal to

$$s_{ijt} = \frac{\exp\left\{\delta_{jt}^{patient} + \mathbb{I}_{\mathrm{PC}}\delta_{jt}^{PC} + \sum_{urban=1}^{6}\left(1-\gamma_{urban}\right)\mu_{ijt}\right\}}{1+\sum_{k=1}^{1175}\exp\left\{\delta_{kt}^{patient} + \mathbb{I}_{\mathrm{PC}}\delta_{kt}^{PC} + \sum_{urban=1}^{6}\left(1-\gamma_{urban}\right)\mu_{ikt}\right\}} \tag{5}$$

and the overall market share of product j in market t can be found by integrating the individual market shares across the individual types, while weighing each type according to its probability in the population. I denote $\hat{P}(D)$ the (empirical) distribution of the demographic characteristics and $\mathscr{N}(\nu)$ the distribution of the unobserved characteristics:

$$\begin{aligned} s_{jt} &= \int_{\nu}\int_{D} s_{ijt}\,\mathrm{d}\hat{P}(D)\,\mathrm{d}\mathscr{N}(\nu) \qquad (6)\\ s_{jt} &= \int_{\nu}\int_{D} \frac{\exp\left\{\delta_{jt}^{patient} + \mathbb{I}_{\mathrm{PC}}\delta_{jt}^{PC} + \sum_{urban=1}^{6}\left(1-\gamma_{urban}\right)\mu_{ijt}\right\}}{1+\sum_{k=1}^{1175}\exp\left\{\delta_{kt}^{patient} + \mathbb{I}_{\mathrm{PC}}\delta_{kt}^{PC} + \sum_{urban=1}^{6}\left(1-\gamma_{urban}\right)\mu_{ikt}\right\}}\mathrm{d}\hat{P}(D)\,\mathrm{d}\mathscr{N}(\nu) \end{aligned}$$

The demographic characteristics are picked from the Medicare dataset. In order to proxy for patients, I use the patient cumulative data available for each physician as a representative consumer for each product (specialty-procedure) combination. Since products are defined at a wider level than physicians, thousands of patient proxies are available for each market. I then sort them randomly and pick twenty observations per market of the following characteristics: per capita income (which varies with every zip code), per capita income squared, average risk score (a variable created by Medicare, which measures the general "healthiness" of patients considering many different elements, from diabetes to cancer), gender (as the percentage of patients that were female seen by each doctor), age (as the average age of patients seen by each doctor).

2.5 Data Analysis

To be able to analyze the margins along which primary care physicians carry out specialty procedures, I first need to define what constitutes a specialty procedure. To do so, for every procedure, I look at the number of times the procedure is carried out by specialists and primary are physicians, respectively, over the entire dataset (~26 million observations across four years). In Figures 2.2 and 2.3 and in supplementary results available upon request, I also analyze what percentage of physicians in primary and specialty care, respectively, carry out any given procedure. I then consider the procedures of interest to be those performed by specialists 50-80% of the time and by the primary care the remaining 20-50%. Robustness checks show that the results are robust independently of the range chosen, but their effect is stronger for tighter ranges. This approach creates a specialization index for each procedure, from 0 to 1. An index value equal to 0 means that the procedure is only carried out by specialists, while an index value of 1 means that it is always carried out by primary care. Therefore, the lower the index value, the more specialized the procedure is.

Having built this index, I can analyze whether physicians, on general, perform procedures within their specialty or not. I observe some clustering in the procedures carried out, with primary care physicians carrying out either mostly primary care procedures (with an average specialization index of at least 0.6) or almost exclusively specialty procedures (with an average specialization index between 0.3 and 0.4). Among those primary care physicians who perform at least one specialty procedure, it is also observed that they tend to perform a large number of specialty procedures. The median procedure carried out by these primary care physicians, as shown in Table 2.1, is one carried out by specialists 60% of the time.

It is clear from this evidence as well as other data analysis reported in the online Ap-

Table 2.1: Percentiles of degree of specialization (the lower the number, the more specialized)

	Percentile
25th percentile	52.06%
50th percentile	63.44%
75th percentile	72.11%
90th percentile	80.99%

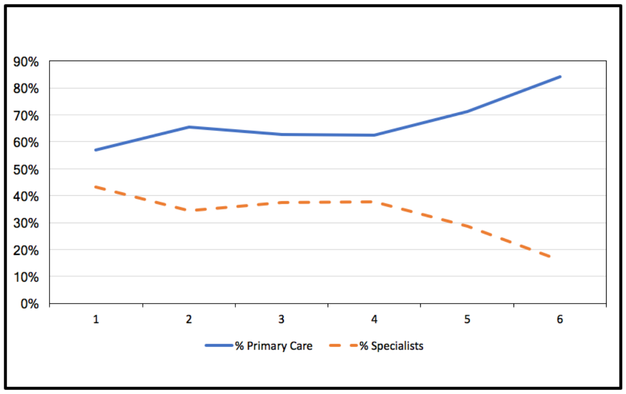
Notes: The variable of interest is an indicator variable, from 0 to 1, indicating the frequency of performance of each procedure by primary care physicians and specialists. This table uses the average of this variable, for each doctor, across all procedures carried out by that doctor. A value of 0 indicates that a doctor performs only specialty procedures, a value of 1 indicates that a doctor only performs primary care procedures. This table only shows the degree of specializations for the doctors who perform at least one specialty procedure.

pendix, that some primary care physicians are able to carry out a large number of specialty procedures. The margin through which they are able to do so, which is the main theory analyzed in this chapter, is how urban or rural the area where the physician practices is.

To be able to understand this better, I focus on procedures carried out by primary care physicians 20-50% of the time and look at the distribution of doctors and services across the urbanity index, by specialization, as shown in Figure 2.2.

For robustness, I restrict my attention to highly specialized procedures, i.e. the procedures carried out by specialists 70-80% of the time and once again look at the distribution of doctors and services across the urbanity index, by specialization, as shown in Figure 2.3.[3]

[3] All the results that are presented in the remainder of this chapter are based on the procedures carried out by specialists 60-80% of the time. All the results are qualitatively robust to different specialization ranges and these robustness checks are available upon request.



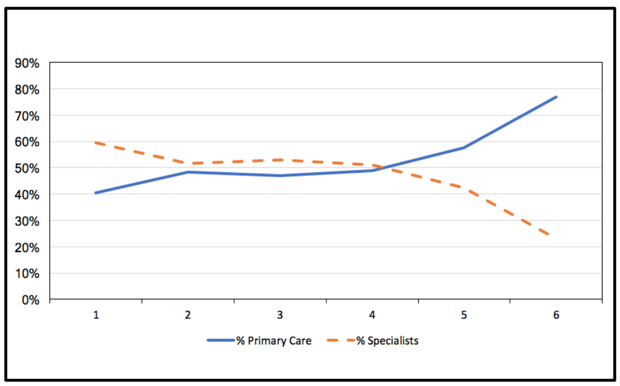
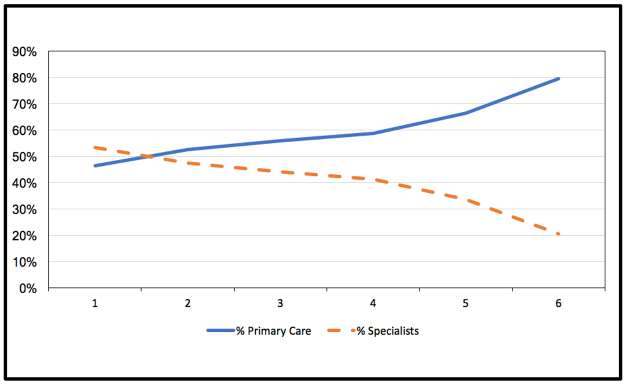


Figure 2.2: Procedures usually carried out by specialists 50-80% of the time

Notes: This figure concentrates on procedures usually carried out by specialists 50-80% of the time. The first figure looks at the percentage of doctors carrying out these procedures (even just once) who are in primary care vs some specialty, across urbanity levels. The second figure looks at the percentage of services provided by primary care vs some specialty, across urbanity levels. The urbanity of the area is an index from 1 to 6, where a higher value denotes a more rural area.

The preceding data analysis documented the following facts. First, specialty procedures are also executed by primary care physicians, who seem to make an informed choice on whether or not to provide specialty procedures. Moreover, those primary care doctors that provide specialty procedures are likely to perform multiple specialty procedures. Finally, primary care physicians in less populated, less urban areas are able to perform more specialty procedures than primary care physicians in more urban, densely-populated places.



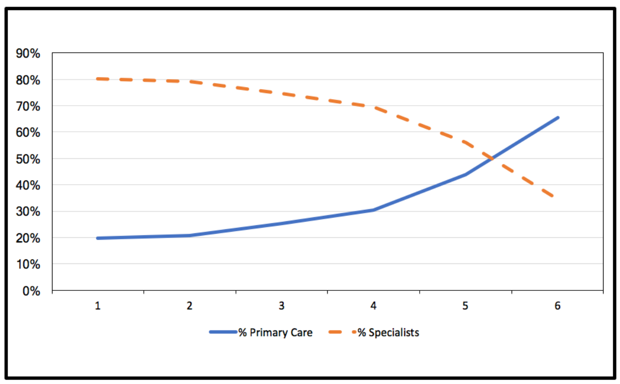


Figure 2.3: Procedures usually carried out by specialists 70-80% of the time

Notes: This figure concentrates on procedures usually carried out by specialists 70-80% of the time. The first figure looks at the percentage of doctors carrying out these procedures (even just once) who are in primary care vs some specialty, across urbanity levels. The second figure looks at the percentage of services provided by primary care vs some specialty, across urbanity levels. The urbanity of the area is an index from 1 to 6, where a higher value denotes a more rural area.

This latter finding hints at a tradeoff in their decision-making on what treatments to offer and give to patients in different locations, supporting the theory of this chapter. The data therefore support the theory that primary care physicians take over more specialty procedures in more rural places, where specialists are not as present as they would be in cities. The remainder of this chapter will focus on analyzing whether primary care physicians are able to use this urbanity margin to take on more remunerative procedures.

2.6 Empirical Evidence and Reduced-Form Results

This Section seeks to provide some empirical evidence as well as discuss some reduced-form results that inform the theory of this chapter. To do so, I restrict my attention to the procedures carried out by specialists 60-80% of the time and by primary care physicians the remaining 20-40% of the time. As previously discussed, procedures are categorized considering the incidence with which all procedures are carried out across all places and years to be able to classify a procedure as a specialty procedure. All level analyses are performed controlling for area-specific characteristics as well as patients' demographics and health characteristics.

First, I analyze whether there is a relationship between the reimbursement fees and the frequency with which a given specialty procedure is carried out by primary care. Second, I control for fixed effects exploiting the time variation in the data since reimbursement fees are changed on an annual basis. I then estimate the effect that changes in the reimbursement fees have on the probability with which a primary care physician carries out a specialty procedure through a logistic regression. I run the estimation both with and without frequency weights. With frequency weights, the higher is the increase in the number of times the more remunerative procedure is carried out, the higher the weight is.

The typical endogeneity challenge present in similar analyses of different industries is less of a concern here due to the focus on Medicare patients. Medicare patients, as a matter of fact, do not have to pay out-of-pocket for the entirety of the bill. For all the procedures considered here, Medicare offers insurance coverage, guaranteeing that patients only have to worry about a co-pay and a co-insurance rate. Therefore, it is highly plausible that patients would not shop around to find a cheaper provider for that particular procedure, but would take the price as given. This would imply that the coefficient on price should be very close to zero.

Nevertheless, there is still the potential of some unobservable effect on the price. To illustrate, consider the fact that choices of physicians are often based on personal matters, such as friendliness of the physician, recommendation from friends or family, or simply him/her being the "family practice of the town." Similarly to a higher-quality product in another industry, this provider could have higher rates that could translate into a higher out-of-pocket cost for patients. This would bias the price coefficient upward, indicating a lower elasticity of patients to prices, when instead the choice of the higher-rate physician would be due to factors that are unobserved by the econometrician. To control for this issue, I use instrumental variables which represent input costs. These costs would increase a physician's pricing menu but not be observed or considered by patients, which is the identifying assumption necessary for the instrument to work. I utilize malpractice insurance reimbursement fees as a proxy for malpractice insurance. Malpractice insurance is a very good proxy for costs: it is higher in cost for higher-cost cities and is higher for higher-risk specialties, which also involve greater costs for machines and equipment. The higher the cost for insurance, the higher the total procedure billing, but malpractice insurance never enters patients' demand functions, as it is as a pure input cost and does not affect other characteristics. I also include the so-called Geographical Adjustment Factors (GAFs), which are cost-of-living adjustments for work, practice expenses, and malpractice insurance, proxying for regional variation in input costs. In the specifications that account for additional heterogeneity, I supplement these instruments with functions of the same instruments, as common in the literature: the interaction term of the work GAF with the practice expense GAF, the square of the work GAF, and the square of malpractice reimbursement units. The coefficient on price once it is instrumented is significant and negative, but still close to zero, as theory would suggest.

To provide some empirical reduced-form evidence supporting this chapter, let me first report the results of a regression of the number of services provided by primary care for specialty procedures on the reimbursement fees, controlling for costs, area-specific characteristics as well as patients' demographics and health characteristics. As previously mentioned, I restrict my attention to those procedures carried out by primary care physicians 20-40% of the time (and by specialists 60-80%). The results are shown in Table 2.2.

These results are consistent with the suggested theory. The geographical adjustment factors control for the cost of living in different areas, which explains the high value on the procedure geographical adjustment (Procedure GAF) coefficient, as an increase of 1 in the geographical practice cost indices is a very high increase. To illustrate, a unit increase in the work and practice indices is equal to double the difference between the maximum and minimum value in the same indices, while a unit increase in the malpractice insurance cost index is roughly equal to the difference between the malpractice insurance cost in Wyoming and the malpractice insurance cost in NYC suburbs. The procedure geographical adjustments are higher, where the cost of living is higher, that is, in cities, so the parameters on the geographical cost indices simply reflect the fact that more populated places lead to higher service counts. The Procedure Reimbursement variable is the reimbursement factor. I find that primary care physicians respond positively to increases in reimbursements, increasing the number of more remunerative specialty procedures they carry out. To be precise, I find that for every unit increase in the reimbursement revenue for a given procedure, equal to about $36, the physician performs that procedure 3 more times.

Another key component of the analysis is the margin of urbanity. The urbanity index value that is left out for comparison is the value attached to the most rural areas. Comparing the parameters, it is easy to see that the more rural the area, the higher the service count of procedures carried out by primary care physicians, as expected.

Table 2.2: Number of procedures carried out by primary care physicians

Variables	$\hat{\beta}$
Procedure Reimbursement	3.33
	(5.44)
Procedure GAF	323.68
	(81.31)
Large Metro w/in MSA	-8.67
	(1.85)
Large Metro	-10.87
	(1.71)
Metro with 250k$\leq pop \leq 1mil$	-6.29
	(1.49)
Metro with 50k$\leq pop \leq 250k$	-2.34
	(1.62)
Metro with 10k$\leq pop \leq 50k$	-0.33
	(1.57)
Constant	-7.63
	(0.29)
Observations	700,855
R^2	0.31

Notes: Linear regression of variables of interest on the number of procedures carried out by primary care physicians. The urbanity of the area is an index from 1 to 6, where a higher value denotes a more rural area. Geographical, procedure, and year dummies are included, as well as demographic controls. Standard errors in parentheses.

Next, I create a variable which takes value of 1 whenever a primary care doctor increases the number of times a given specialty procedure is provided from a year to the next, 0 otherwise. I then run a logistic regression to see whether an increase in the reimbursement rate of a given procedure raises the probability of a primary care physician increasing the number of times she carries out that procedure. The results in Table 2.3 show that an increase in the reimbursement rate of one value unit for a given procedure, equal to roughly a $36 increase, increases the probability of primary care physicians increasing the number of times that procedure is carried out by about 16.6%. Frequency weights play an important role in this estimation. Accounting for frequency weights, so that a higher weight is placed on physicians who increase the number of procedures carried out more, an increase of one relative value unit in a given procedure, equal again to about $36, leads to a 45.5% higher probability of the primary care physician increasing the number of times that procedure is carried out.

For robustness, I widen the set to the procedures carried out by primary care physicians between 20 and 50% of the time (and by specialists 50-80% of the time). The results are presented in the Appendix Section A.11 and show that the qualitative results are the same.

2.7 Structural Model Results

I run four specifications to estimate the model discussed in Section 2.4: the standard random coefficients logit model, with and without Chamberlain's optimal instruments, a specification that uses the demographic variation in the data to estimate the random coefficient, and finally a random coefficient logit model using both Chamberlain's optimal instruments and the demographic variation in the data. Table 2.4 reports all results on the analysis of primary care physicians increasing their share at expense of specialists along the urbanity index. All specifications utilize the time variation in the data to identify the parameters. Recall that the relative value units are set by policymakers annually.

Table 2.3: Logit: y=1 if primary care physicians increase the number of specialty procedures carried out - 20-40%

Variables	(1)	(2)
Change in Procedure Reimbursement	0.17	0.46
	(0.02)	(0.003)
Change in Malpractice Reimbursement	-1.69	-3.39
	(0.06)	(0.01)
Change in Practice Reimbursement	0.25	0.63
	(0.01)	(0.001)
Change in Procedure GAF	9.25	37.02
	(1.78)	(0.19)
Change in Malpractice GAF	-0.04	0.29
	(0.02)	(0.003)
Change in Practice GAF	-3.20	-12.57
	(0.71)	(0.08)
Constant	1.94	2.75
	(0.004)	(0.004)
Frequency Weights	NO	YES
Observations	1,677,036	1,677,036

Notes: Logistic regression of variables of interest on whether or not primary care increases the specialty procedures provided, with and without frequency weights. The procedures included are those that are carried out by primary care physicians, on average, between 20 and 40% of times as suggested by the specialization index previously discussed. Year dummies are included. Standard errors in parentheses.

A few results should be discussed. First, the price coefficient is very close to zero, but negative, as expected in the previous discussion in Section 2.6. Second, the urbanity of the area emerges again as a key margin for primary care physicians. The five variables which look at the interaction of the reimbursement with the urbanity index generate estimates that have to be compared with the reference variable, which value indicates the most rural areas. The results support the empirical evidence shown in Section 2.6 that primary care physicians are able to increasingly take on a higher share of specialty procedures, the more rural the area.

Since all the specifications are variation of the logit model, the Reader should recall that the estimated coefficients on the interaction of the reimbursement with the urbanity index, $\hat{\beta}_{rvu}$, are not exactly equal to the parameters of interest, which are instead equal to: $\gamma_{urban} = \exp\left\{\hat{\beta}_{rvu,urban}\right\} - 1 \ \forall \ \text{urban} = 1, ..., 6$. To aid the Reader with the interpretation of the coefficients, a summary of the coefficients of interest γ_{urban} are shown in the summary Table 2.5, switching the point of view to set the most urban counterparts as the point of reference. Bearing this in mind, I find that an increase in one relative value unit, once again equal to about $36, primary care physicians are able to increase their share in specialty procedures between 7 and 15% in more rural areas compared to their most urban counterparts, at the expense of specialists. These results provide some evidence that the urbanity is a key margin along which primary care physicians can use the lower competition coming from specialists to increase their reimbursements by carrying out the specialty procedures themselves rather than referring them to specialists somewhere else. The most affected areas are very rural areas (the dummy of reference, which value is higher than almost every other more urban value) and in small metropolitan areas (which is the only estimate higher than the dummy of reference). Primary care physicians' ability to increase their shares at the expense of specialists along the urbanity index is very robust and significant across all specifications.

Table 2.4: Primary Care Physicians Turn Specialists

MEAN UTILITY	(1)	(2)	(3)	(4)
Price	-0.001	-0.001	-0.001	-0.001
	(0.00)	(0.00)	(0.00)	(0.00)
Procedure Reimbursement	-0.067	-0.080	-0.119	-0.046
	(0.20)	(0.01)	(0.05)	(0.01)
Procedure Reimbursement, Large Central Metro	-0.116	-0.115	-0.111	-0.106
	(0.02)	(0.01)	(0.01)	(0.01)
Procedure Reimbursement, Large Fringe Metro	-0.026	-0.030	-0.023	-0.039
	(0.01)	(0.01)	(0.01)	(0.01)
Procedure Reimbursement, Medium Metro	-0.040	-0.040	-0.030	-0.031
	(0.02)	(0.01)	(0.01)	(0.01)
Procedure Reimbursement, Small Metro	0.031	0.029	0.039	0.033
	(0.01)	(0.01)	(0.01)	(0.01)
Procedure Reimbursement, Micropolitan Area	-0.048	-0.048	-0.031	-0.040
	(0.02)	(0.01)	(0.01)	(0.01)
Medical Doctor Degree	-0.432	-0.463	-0.431	-0.538
	(0.03)	(0.02)	(0.02)	(0.02)
Number of Primary Care Physicians Around	-0.002	-0.002	-0.002	-0.002
	(0.00)	(0.00)	(0.00)	(0.00)
Number of Primary Care Physicians Doing Specialty Work	0.575	0.656	0.575	0.915
	(0.21)	(0.07)	(0.07)	(0.07)
Constant	-6.405	-6.447	-6.392	-6.607
	(0.18)	(0.03)	(0.03)	(0.03)
RANDOM COEFFICIENT, Procedure Reimbursement SD	0.120	0.120	0.155	0.080
	(0.11)	(0.00)	(0.01)	(0.00)
Demographics	NO	NO	YES	YES
Optimal Instruments	NO	YES	NO	YES
Observations	76,133	76,133	76,133	76,133

Notes: The table reports the results from the structural estimations described in Section 2.7. Standard errors in parentheses. Estimates of control variables are omitted from the table to facilitate the Reader and are available upon request.

Table 2.5: Change in Physicians' Weight in Consumers' Utility with Respect to Physicians in Large Metro Areas, γ

γ	BLP	BLP Optimal Instruments	BLP Demographics	BLP Optimal Instruments and Demographics
γ_2-Fringe Metro	9.42%	8.87%	8.80%	6.92%
γ_3-Medium Metro	7.90%	7.79%	8.44%	7.79%
γ_4-Small Metro	15.84%	15.49%	16.18%	14.91%
γ_5-Micropolitan	7.04%	6.93%	8.33%	6.82%
γ_6-Rural	12.30%	12.19%	11.74%	11.18%

Notes: This table shows the increase in the primary care physician's utility weight on the consumer utility, γ , along the urbanity index compared to the most urban classification (urban=1, large metro area), for all specifications considered in this chapter. The four specifications are the following: a random coefficients model that uses the BLP (1994) algorithm, the second one uses the same model but includes Chamberlain optimal instruments, the third one uses the same model but lets the random coefficients depend on the empirical distribution of demographic characteristics, and the final one includes both the optimal instruments and the demographics in the estimation.

2.8 Conclusions and Future Work

Using data on the insured population of Medicare, this chapter has provided evidence for a supply-induced mechanism in the demand for healthcare in the US. First, it has documented the novel fact that primary care physicians are able to carry out an increasing share of specialty procedure in more rural areas of the United States, where specialists are fewer. Second, this chapter has found that primary care physicians increase their share in specialty procedures more, the more lucrative they become, and are able to do so more, the more rural the area they practice in. From the reduced-form results, this chapter has found that an increase in one unit of reimbursement for a given procedure, equal to an increase in reimbursement of about $36, leads to over a 45% higher probability of primary care physicians providing a higher number of the more lucrative procedure. Structurally, this chapter has estimated that the same \$36 reimbursement increase for a given procedure leads to an increase in the primary care physician share in that specialty procedure by 7-15% more in less urban areas compared to their most urban counterparts, at the expense of specialists. Small metropolitan areas (with a population between 50,000 and 250,000 people) and very rural areas (with a population smaller than 10,000 people) are the most affected.

This chapter has also been the beginning of a more comprehensive research project analyzing physicians' choices bearing in mind how 1) specialty differences are crucial when modeling their behavior, 2) reimbursements are a key income component that has been largely ignored in many analyses, and 3) the urbanity of the area comes into play in many different ways, and it is clear from the results found in this chapter that physicians practice differently according to where they are. Chapter 3 keeps these factors in mind when analyzing the determinants of physicians' location choice, with a focus on the rural shortage of physicians. Other ongoing projects analyze the substitutability of primary care physicians with nurse practitioners, the effect of nurse practitioner regulations on primary care entry, and finally the impact of the physician workforce on the population's health.

Despite the many projects that have sprung from this analysis, many questions arise that still have to be addressed. First, a natural extension to this chapter is to analyze the supply side of this issue. In particular, primary care physicians need to make investment choices to be able to offer specialized treatments. Second, related to Chapter 3, it would be interesting to study how these financial incentives influence medical students' choices. It is plausible that medical students have adjusted their specialty choices since the implementation of the fee-for-service system based on the possibility to get different financial benefits from different locations. This question is important to explain the decrease in students' interest in primary care specialties following the 1992 change in Medicare pricing. This hypothesis is able to rationalize the wage and offering differential across specialties, while also showing that the ability for primary care to perform more specialized procedures in less urban areas is the result of the pricing mechanism described in this chapter. Therefore, this theory would be able to explain not only the general decline in the interest for primary care specialties, but also the geographical shifts in the primary care distribution in the country.

Finally, as suggested in the introduction, this chapter strongly relates to the arguments discussing the relationship between a fee-for-system payment scheme and overutilization. This chapter has provided a key insight to the issue of overutilization by showing that a change in financial incentives also leads to a reallocation in the providers carrying out the same procedures. Considering the primary care physicians' increase in specialty procedures caused by the increased financial incentives as overutilization would overlook the fact that this increase comes at the expense of specialists, as analyzed in this chapter. Therefore, this chapter has provided evidence that it is key to consider two complementing effects caused by fee-for-service: a reallocation in the procedures carried out by each specialty for a given total number of procedures, as shown here, and the increase in the number of total procedures carried out overall without an apparent increase in patients' health issues, the latter of which is not analyzed in this chapter and should be subject to future research.

Chapter 3

The Determinants of Physicians' Location Choice: Understanding the Rural Shortage

3.1 Introduction

A long-standing challenge in the US health care system is the provision of medical services to rural areas, where 25% of the population live, but only 10% of physicians operate.[4] An extensive discussion on academic and media outlets alike has taken place regarding the need for physicians in many areas of the United States, which are dubbed as Health Professional Shortage Areas (HPSA). With roughly 60 million Americans living in rural areas, it is evident that rural Americans make up for a major part of the affected population. Policymakers have tried to bring more doctors into rural areas, most notably with loan forgiveness programs, which have been further incentivized through their tax exclusion via the Affordable Care Act. As a further incentive, higher fixed salaries are also usually offered to physicians who decide to practice in rural areas. While the number of primary care physicians who practice rurally has increased, the physician shortage is still a very real problem, especially for some (rural) areas. Therefore, fully understanding the different factors that affect physicians in their geographical choices is important in designing policies that aim for a more even distribution of physicians in caring for the American population.

This chapter develops a model of physicians' location choices and uses it to explore the impact of policy changes, such as loan forgiveness and salary incentives, on the geographical distribution of physicians. I focus on the choice of the first job following residency, therefore analyzing the location choice once the specialty is already picked. While studies have been done regarding the choice of residency, the so-called medical match (for instance, see Agarwal 2015), this chapter does not look at the specialty choice along with location. The decision to take the specialty as given allows me to ignore the issue

[4] See, among others, Aaron Carroll, "A Doctor Shortage? Let's Take a Closer Look," *The New York Times*, November 7, 2016 as well as Gary Hart's interview, Ann Harrington, "Training More Country Doctors," *Fedgazette*, October 12, 2017.

of residency slots available as well as all the details of “the match.” I build a structural spatial equilibrium model in which physicians are heterogeneous along their specialty, demographics, and quality ranking. Identification of the parameters of interest (income) is challenged by the possible correlation between unobserved characteristics of location and wages, as offered wages are higher where amenities are fewer. To overcome this issue, I collect micro-level data from physicians’ directories on doctors’ medical school, residency, and first job choices. This wealth of information and structural methods of demand à la Berry, Levinsohn, and Pakes (1995) allow me to back up the unobserved characteristics and identify the parameters of interest exactly.

The differentiation between specialty groups is shown to be key in policy design. As shown in Chapter 2, the mix of treatments that primary care physicians and specialists perform varies along the urbanity index. In particular, primary care physicians perform more specialist procedures (and therefore receive higher reimbursements) in rural areas, due to the lower competition coming from specialists in those areas. Capturing this heterogeneity allows policies to be designed more efficiently by targeting the groups of physicians who would respond the most. Moreover, the information on physicians’ quality ranking enables me to vary the job choice set according to each physician’s quality level. This is important in the design of choice sets as the set of jobs available to each physician critically depends on the physician’ quality. There is a vast literature addressing how misspecification of the choice sets leads to choice model misspecification. Gopinath (1995) provides a good overview of the theoretical and empirical issues on this topic.

Several factors affect the location choice. I allow physicians to respond to their full real income (therefore accounting for salary, reimbursements, rent, malpractice insurance, and student loan repayment), as well as to amenities and heterogeneous location preferences. One immediate trade-off related to physicians’ incentives is the higher salary offered in rural areas to compensate individuals for the typical lack of amenities (see, for example, Lee 2010). However, the urbanity of the area not only influences the amenities of the area but also the competition from doctors in surrounding areas, which in turn affects the procedures that physicians can carry out. Physicians' revenue stream is composed of two parts: a salary part that behaves as theory would predict by increasing salaries in less desired areas, and a reimbursement part. This latter part depends only on the procedures carried out and is adjusted for the cost of living, meaning that the rate adjustments are greater for physicians in urban areas than for those in rural areas. Moreover, the number and type of services provided also vary along the urbanity index. Chapter 2 shows that each physician's market share for a given treatment in a particular location depends on the number of primary care physicians and specialists performing the same treatment in that market. As a result, primary care physicians in rural areas are able to increase their income by carrying out more specialized procedures. Since the fee-for-service part of their income does not depend on their specialty but only on the procedures they carry out, and since such specialized procedures have increasingly been reimbursed more than primary care procedures, this creates incentives for primary care physicians to work in rural areas. Therefore, these different components of income and how they are affected by the distribution of physicians must be accounted for. On the supply side, I allow physicians' income to respond to the employment of physicians of either type, bearing these facts in mind.

I also allow for a home bias toward the place where the doctor completed his or her residency, based on data evidence. To be able to control for quality, I match the ranking of the medical school (based on the average score of MCATs, among other things) and the ranking of residency to proxy for physicians' quality ranking. As mentioned beforehand, quality not only is important as a demographic variable but also is key in the choice set definition.

Next, I analyze what factors affect their geographical distribution the most. Firstly, the results suggest that the two specialty groups respond to compensation differently, as specialists are more elastic to both net income and amenities. Both groups, however, enjoy higher net incomes and higher amenities. I find that top-50 residents respond more to both income and amenities, while foreign physicians are not systematically different from Americans. Persistence in location choice is key, as I find that primary care physicians are about 3.8 times more likely to work in the same state as their residency and about 3.4 times more likely to work in the same hospital referral region as their residency. Similarly, specialists are 2.8 times more likely to work in the same state as their residency and about 3.6 times more likely to remain in the same hospital referral region for work. I am able to reject that retention values can be the same between primary care physicians and specialists. I also find that top-50 residents in primary care are 0.4 times more likely to remain in the same state as their residency for work, but they are 1.5 times less likely to remain in the same area as residency. Conversely, I find that top-50 residents in specialty care are 0.3-0.4 times less likely to be retained within the same state and area of residency. Comparing these results to the labor literature, I find a very interesting result. While all physicians are clearly high-skilled workers, primary care physicians display the same persistence in location choices as unskilled workers. Diamond (2015), for example, reports a semi-elasticity of retention for high-skilled individuals to remain within their state of birth equal to 2.6. That estimate is closer to the values I find for specialists, but much lower than the values that I find for primary care physicians. This shows that there are extremely important differences not only across occupation types, but also within occupations that might be ignored in current analyses.

Finally, I use the model to analyze the performance of current policies targeted at bringing physicians to rural areas. I find that 0.5% more primary care residents and 1.3% more specialists have picked rural areas due to loan forgiveness alone. Monetary incentives in the form of bonus payments averaging $7,500 are responsible for a further 0.2% increase in primary care physicians and 0.1% increase in specialists. By retargeting the spending currently used for loan forgiveness to higher salary incentives for rural employment, I find that almost 6 times more primary care physicians would pick rural areas compared to the effect of loan forgiveness. Since primary care physicians are the main physician category that currently provides medical care to rural areas, and since they do not need a particular infrastructure to do so, these results suggest that policymakers should retarget spending from loan forgiveness to salary incentives and that offering salary incentives to primary care physicians only would be even more effective. The average quality of the physicians attracted under these higher salary incentives is also better compared to loan forgiveness. Another possible policy intervention suggested by the high persistence in physicians' location choices is the use of these monetary incentives to create rural residencies. Since the residency choice is not directly modeled in this chapter, this question is outside the scope of this chapter but will be addressed in future work.

The chapter proceeds as follows: Section 2 introduces a brief literature review, Section 3 presents a few definitions and descriptive facts, Section 4 describes the many data sources used in this chapter, Section 5 examines the model, Section 6 discusses the estimation techniques, Sections 7 presents and discusses the results and their implications, Section 8 discusses the counterfactuals run, and Section 9 concludes.

3.2 Literature Review

This chapter contributes to three strands of literature: it complements and extends the old microeconomics literature on physician location and geographical distribution, it provides more insight to the health economics literature on physicians' response to incentives, and it relates and extends the labor literature on location choice of skilled workers.

First, this chapter contributes to the strand of literature on physician location. Cooper et al. (1975), Leonardson, Lapierre, and Hollingsworth (1985), Steele and Rimlinger (1965) are all papers that have provided evidence for an uneven distribution of physicians. Nevertheless, the papers in the literature provide some data evidence through surveys and reduced-form analyses without providing a mechanism for their location choices. Previous discussion on the topic of location choice has mainly focused on the tradeoff between amenities and salary, as in Lee (2010). Lee provides evidence of higher salaries rurally than urbanely and provides a theory that the increased salary has to make up for the lack of amenities. There has also been a lot of attention regarding the shortage of physicians and the distribution of physicians' location, including Kirch, Henderson, and Dill (2012) and Cooper et al. (2002). This chapter complements their analysis by providing the major components that affect the choice of physicians' location and possible solution to the physicians' shortage. There has also been a lot of attention recently regarding the shortage of physicians and the distribution of physicians' location, including Kirch, Henderson, and Dill (2012) and Cooper et al. (2002). This chapter complements their analysis by providing the major components that affect the choice of physicians' location and possible solution to the physicians' shortage. Kulka and McWeeny (2018) also structurally analyzes physicians' location choices and evaluates policies the induce physicians to move to rural areas, but my analysis differs in several important respects.[5] First, I differentiate across specialty groups. Second, I make use of individual-level data on physicians' training and work history to estimate the value of retention from remaining within the same area as their residency and to define the choice set according to the physicians' quality. Finally, I employ a more detailed measure of compensation that includes net income that also depends on reimbursements, rent, malpractice insurance, and student loan repayments.

This chapter also contributes to the strand of health economics literature discussing how physicians respond to financial incentives, basing part of the analysis on Chapter 2. Chapter 2 provides evidence for a supply-induced demand mechanism for more remunerative treatments. It finds that primary care physicians are able to take on more specialist services in less urban areas, where they gain higher market shares due to the lower number of specialists in close proximity. In particular, the increase in the weight of the primary care physicians' financial interests in the consumer utility ranges between 7-16% compared to physicians in large metropolitan areas, at the expense of specialists. More generally, Lee (2010) shows that higher rural salaries provide an incentive for physicians to trade off lower amenities for higher compensation. There has been an extensive literature on the response of physicians to financial incentives in a hospital setting (Acemoglu and Finkelstein 2008, Finkelstein 2007) , in managed care (Lori 2009), for specific procedures (Gruber & Owings 1994, Grant 2009, Shrank 2005, Jacobson 2006), and across geographical locations (Clemens and Gottlieb 2014). This chapter complements this literature by including financial incentives in the analysis, without only focusing on wages, but also by analyzing how physicians trade off monetary incentives for non-monetary ones.

Since physicians make up for a very important occupational group, this chapter also complements the location choice strand of the labor literature across skill levels, includ-

[5] I learned of their paper after completing a first draft of my chapter.

ing, but not limited to, Diamond (2015) and Colas (2018). Of course, physicians are all part of skilled labor. Nevertheless, this chapter provides insight on within-occupation differences across types and shows that, at least for physicians, the differences between within-occupation types are just as important as those between the unskilled and the skilled. This chapter also complements the structural labor literature on location choice and market structure, such as Dunne et al. (2013).

Methodologically, this chapter bases itself mostly on Berry, Levinsohn, Pakes (1995, hereafter: BLP). While BLP has been one of the most predominant tools in the literature for demand estimation, this chapter applies the tool to a location choice setting. Thanks to the differentiation across locations and the presence of physician cohorts looking for a job at the same time nationally, I utilize this algorithm to identify what drives the choice of physicians' location, matching the share of physicians picking one location over all the physicians looking for a job in the same year. I include demographic characteristics of physicians and integrate over the empirical distribution of such characteristics to identify random coefficients. The information on physicians' quality ranking enables me to vary the job choice set according to each physician's quality level. This information is then used in the design of choice sets as the set of jobs available to each physician critically depends on the physician' quality. This is key as a misspecification of choice sets would lead to choice model misspecification.

3.3 Data

The geographical unit of study is a hospital referral region (HRR), as defined by the Health Resources & Services Administration. Therefore, any location-level characteristics are estimated for these geographic areas through data at the county-, metro-, and zip-code level, allocated to HRRs by averaging or aggregating the values up to the HRR-level according to their geographical location. The goal of HRRs is to define areas that are self-contained markets for primary care, so that the majority of patients living in that area go to primary care physicians within that area. The urban/rural classification follows the U.S. Census Bureau definition according to the 2010 Census criteria.

The primary source of data for this chapter comes from the Centers for Medicare & Medicaid Services (CMS). The Physician and Other Supplier Public data provides information on services and procedures provided to Medicare beneficiaries by physicians. It contains information on utilization, actual Medicare reimbursement, and submitted charges. Each line of the dataset is indexed by a National Provider Identifier (NPI), which identifies each doctor in the dataset, by a Healthcare Common Procedure Coding System (HCPCS) code, which identifies every procedure carried out by each doctor, and by the place of service, indicating whether the procedures were carried out in a facility setting or not. The data is based on information from CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service program. The data are available for calendar years 2012 through 2016 and contain the universe of physicians taking part in Medicare Part B for the fee-for-service population. There are a little over 40 million observations in the dataset across over a million of physicians in the panel.

Despite the wealth of information on payment and utilization for Medicare Part B services, the dataset has a number of limitations. The data may not be representative of a physician's entire practice as it only includes information on Medicare fee-for-service beneficiaries. However, since Medicare influences the payment system of 80% of physicians (Clemens & Gottlieb (2017)), this data allows for the analysis of physicians' behavior under this payment mechanism, which is then relevant for the greatest majority of doctors in the country. In addition, the data are not intended to indicate the quality of care provided and are not risk-adjusted to account for differences in underlying severity of disease of patient populations. To counter this, demographic data on patients' riskiness and incidence of diseases will be included in the estimation. Despite these limitations, some positive characteristics should be highlighted. First of all, the fact that all beneficiaries are covered by Medicare eliminates the issues related to the status of insurance of the beneficiaries. In particular, it allows me to abstract from other endogenous characteristics related to the insurance status of beneficiaries when a full dataset (not Medicare only) is used. Moreover, it also allows me to ignore the network effects of different insurance policies as well as their different payment plans. In practice, therefore, this dataset provides a more homogenous universe of insured individuals who receive different treatments according to the condition that they have. Once fixed effects are accounted for, then, these data are perfect for the question at hand.

As far as the illness and disease distribution is concerned, average beneficiary risk scores are provided on the "Medicare Physician and Other Supplier Aggregate Table" (i.e., one record per NPI) to provide information on the health status of the beneficiaries the providers serve for every year of interest together with the rate of incidence of a number of diseases and illnesses among the patients seen by each physician for every year. Therefore, this can account for the average health of the patients visited by each physician.

For this to work, it is important to recall that almost the universe of physicians participates in Medicare (and I will observe the physician as soon as they have one patient enrolled in Medicare Part B). To be precise, over 91% of physicians accept new Medicare patients and 96% of Medicare seniors have access to care through their physicians/clinic. Almost 92% of Medicare fee-for-service patients can get an appointment for routine care as needed.

To understand when the physician chooses their first job, I need to know when they finish their training. To do so, I use two more datasets. First, I get all the data from Medicare Physician Compare. Since it is a file created by Medicare, I can match physicians through the NPI. This directory allows me to see their graduation year as well as their medical school for about half of the physicians. Unfortunately, this dataset seems to not report the medical school name for many physicians, by absorbing all of them under "Other." To resolve this issue and be able to account for their residency training as well, I scrape data from the internet directories, in particular Doximity.com, where physicians publish a wealth of information regarding their training and affiliations. I am able to then have a sample of physicians scraped off the internet matched not only to their specialty and office address, but also to their graduation year, medical school, residency, internship and fellowship participation, among other characteristics. From their graduation year, I add the number of years of residency depending on their specialty, as well as an extra year each if they do a year of internship or fellowship. Having done this, I know the year they pick their first job, and I then select out those that pick their first job between 2012 and 2016, to be able to match the variables in the Medicare data. I call the full panel I created the "Physician Work History Panel."

A selected sample of variables from the Physician Work History Panel is available in Table 1 to provide the Reader with a flavor of the collected data.

To have a proxy of the level of quality/skill that physicians could be characterized by, I use the US News rankings for medical schools, by specialty. Moreover, I use the Doximity Residency Navigator ranking to proxy for the quality of the residency program, by specialty. Recall that each physician declares their specialty and I am able to control for multiple if they identify with more than one. This allows me to identify a normalized ranking of their medical school and residency, as well as to know whether they have attended a

Table 3.6: Physicians Work History Panel

	Primary Care	Specialists
Number of Residents	9,691	22,068
Years in the Panel	2012-2016	2012-2016
Locations Chosen Between 2012-6	305	305
% with First Job in Big Metros	60%	70%
% with First Job in Small Cities	30%	25%
% with First Job in Rural Areas	10%	5%
% that Completed Residency in Big Metros	58%	75%
% that Completed Residency in Small Cities	31%	24%
% that Completed Residency in Rural Areas	1%	1%

Notes: The Physician Work History Panel is a dataset that I created and that provides physician-level data on their training and on the work they currently carry out. The Panel is created through two main data sources: first, I use the Medicare Part B Utilization and Payment data; second, I scrape physician directories (mainly Doximity.com) to be able to determine their medical training (medical school, , residency). I then use the medical school information to infer the level of student debt they would be facing and I collect Bureau of Labor Statistics data on wages by occupation title to collect information on salaries. While this panel covers almost the universe of physicians, I focus on residents that finish residency and enter the medical job market in this chapter. More details on the data collection and sample validation are available in the text and appendix. There are 306 HRR in the US.

top 50, top 30, top 50 school and residency, as well as whether or not they attended a school or residency in the bottom quarter percentile of the rankings. Moreover, even though I do not observe physicians' immigrant status, I can get insight from the medical school they attended. This is interesting because foreigners can obtain a visa waiver if they practice in health professional shortage areas or medically underserved areas. I match the medical schools I observe to their addresses and mark those outside the United States, assuming that a person that studied abroad for medical school is, in fact, foreign. The foreign parameter would be, if anything, understated, since I cannot observe immigrants that migrated prior to medical school, but it should be a good enough proxy for the analysis at hand. By including this in the analysis, I am able to see whether there is, in fact, a higher choice of rural placements by foreigners to be able to take advantage of visa benefits.

The other crucial variable for the analysis is the salary received by physicians. For this, I utilize the Occupation Employment Statistics (OES) at the Metropolitan Statistical Area

(MSA)-level for the main occupational divide (primary care vs. surgeons) and subspecialties defined by BLS. The fixed salary data gives an idea of the incentives that physicians face from a pure salary perspective, but they do not include the reimbursement amounts dependent on fee-for-service income. As per Chapter 2, this reimbursement highly depends on the procedures carried out, but these in turn depend not only on the specialty that carries them out, but on the location where the physician is located as well. For this reason, I believe that it is important to consider both income sources in the analysis.[6]

The location characteristics included in the amenity index come from many different sources: County Business Patterns (2012-2016), Federal Bureau of Investigation crime reports (2012-2016), Environmental Protection Agency Air Quality Index (2012-2016), Census of Governments (2012), National Center of Education Statistics, American Community Survey (2012-2016). Refer to section 6.1 for a more complete discussion on the amenity index estimation.

Finally, the choice of a location that displays a shortage of physicians is often associated with high benefits in terms of loan forgiveness. Since my entire dataset is post-Obamacare (when these benefits became higher and tax-deductible), the control for those areas designated as health professional shortage areas captures the loan forgiveness effect. To capture the benefit given by this particular element, I match the medical schools to their tuitions and calculate the amount of student debt that the resident would be facing. The medical debt then disappears as an expense if they were to choose areas offering loan forgiveness.

The sample can explain almost the entirety of the variance in the data, with an R^2 of 93.74% for primary care physicians and 96.47% for specialists. Notice that the sample should not display a perfect fit. As a matter of fact, since the data is based on the Area

[6] Recall the discussion in section 3.2.

Table 3.7: Physicians Work History Panel vs. Leading Data Source

	Physician Work History Panel	Leading Data Source	%
Total Year 3 Residents	31,759	37,617 (Board)	84%
2012 Primary Care Population	198,310	237,346 (AHRF)	84%
2013 Primary Care Population	201,527	242,955 (AHRF)	83%
2014 Primary Care Population	203,445	244,638 (AHRF)	83%
2015 Primary Care Population	205,064	245,983 (AHRF)	83%
2016 Primary Care Population	186,312	247,069 (AHRF)	75%

Notes: The Physician Work History Panel is a dataset that I created and that provides physician-level data on their training and on the work they currently carry out. The Panel is created through two main data sources: first, I use the Medicare Part B Utilization and Payment data; second, I scrape physician directories (mainly Doximity.com) to be able to determine their medical training (medical school, , residency). I then use the medical school information to infer the level of student debt they would be facing and I collect Bureau of Labor Statistics data on wages by occupation title to collect information on salaries. While this panel covers almost the universe of physicians, I focus on residents that finish residency and enter the medical job market in this chapter. This table provides one of many validation exercises to compare the Physician Work History Panel to commonly used data sources for similar statistics. Since I do not have access to any dataset that measures the number of residents on the medical job market by year, I approximate it by the number of Year 3 Residents. Notice that some Year 3 Residents continue their training. Therefore, the leading data source should provide a slightly higher value than the number of residents in my panel, as it is indeed true. Next, I also show in this table how the Physician Work History Panel compares in terms of primary care physician population. To do so, I utilize the Area Health Resource Files by county and I aggregate my data up to the county level to enable a comparison. The Physician Work History Panel is able to reproduce the levels and changes in the physician population closely. Similar statistics are true for specialists as well. More details on the data collection and sample validation are available in the text and appendix.

Resource File data, residents and non-degree primary care physicians are included in the estimates, while my sample excludes them. I also perform some validation exercise on the whole population of primary care physicians and specialists by year, by looking at the Area Health Resource File by county, specialty, and year. Table 2 reports a sample of the results. Overall, the sample considered can explain about 85% of all leading data sources.

Finally, I also checked the retention rate in the data vs. in the sample. My sample produces a within-state retention of 51.4% overall, while the data displays a 54% state retention nationally, further confirming the sample fit.

3.4 Descriptive Facts

3.4.1 Definition of Income

Income in this chapter is calculated using five elements. First, I include both reimbursements and salaries to their total revenues. Second, I subtract from their total revenues three types of expenses: average housing cost in their area, malpractice insurance payments, and student loan repayments.

Reimbursement Much of the health literature focuses on analyzing hospitals and physicians in a hospital setting. While physicians in my dataset can indeed have hospital affiliations, it is important to differentiate how I define their income. Since hospitals behave completely in a different manner regarding reimbursements, I focus on aggregating reimbursement from CMS Medicare Part B data, which excludes hospital bills. This is particularly important because common practice for hospitals is to file all reimbursements for all physicians, and wages paid out to the physicians directly employed by the hospital will simply be adjusted for them.

To be able to combine the effect of receiving reimbursements and wages, I therefore single out reimbursements billed for outpatient procedures, which are billed directly and paid out directly to the doctors. These actually make up for a high portion of aggregate health expenditures, as shown in 1. Since they constitute a substantial portion of their income, physicians internalize them in their decision-making.

Salaries On the other hand, salaries are obtained through the Bureau of Labor Statistics and do not include reimbursements. BLS collects its data through a survey of employers that only report the salary paid. Any amounts billed independently by physicians is not included in the estimate. Self-employed physicians are not included in the wage estimates by BLS. I observe whether or not the physician is in a facility (hospital or clinic) or in an office setting and I am therefore able to differentiate between the two types of physicians for robustness.

Housing costs Housing costs are obtained from the Census American Community Survey, at the zip-code level. Average housing costs are calculated for individuals with incomes higher than $70,000. I focus on owner costs and use the average between mortgage- and non-mortgage-holders.

Malpractice insurance Malpractice insurance costs are estimated according to the malpractice reimbursement rates set by Medicare. In the future, I plan on adjusting these based on observed insurance rates.

Student Loans Student loan repayments are estimated in the following manner. First, I match each individual to the medical school he or she attended. Second, I match the medical school to the tuition cost for the four years of medical school, as available through their "Tuition and Rates" page online. Third, I follow the very common 10-year repayment plan most students would be on to calculate the average annual student loan repayment. According to the plan, the average interest rate is 6%, which is what I use in this chapter. The interest starts accruing from year one, but payments are deferred until after residency. While residents face the choice to start repaying loans during residency, very few do. Since I do not know who does, I assume everybody starts repaying their loans following residency. For areas defined as health professional shortage areas, this cost is set to zero, assuming that residents deciding to move to these areas, would indeed remain for the years necessary to have their loans forgiven.

3.4.2 Reimbursement

This section briefly walks the Reader through the way reimbursements are set and how they vary on an annual basis.

The current (since 1992) fee-for-service system is called the Resource-Based Relative Value Scale (RBRVS). The system was based on some initial rates and geographical adjustment factors, which would be reviewed on an annual basis by the RVS Update Committee (RUC). The RUC was meant to only have an advisory role, but its recommendations are accepted 97% of the time, making it *de facto* the fee-setting organization.

The Reader should bear in mind that the fee-for-service system is not new to 1992. The system before, the Usual, Customary, and Reasonable (UCR) system, was still based on a fee-for-service reimbursement; however, these reimbursements were not standardized across doctors and tractability was not possible also due to lack of information on individual pricing. This is what prompted discussions at the beginning of 1990 to reform it. This chapter shows that the new pricing system exacerbated the issue, leading to a change in doctors' decision making. Moreover, it allows the researcher to be able to estimate the impact of this pricing on physicians' choices due to the fee standardization (and its availability publicly).

For each procedure j in a geographical area-year t, the reimbursement is equal to:

$$Reimbursement_{jt} = Constant_t * RVU_{jt} * GAF_t \tag{7}$$

The constant only depends on the year and is equal across specialties and procedures. The relative value units change according to the procedure as well as the year, and the geographic adjustment factors (GAFs) depend on both the area and the year.

The constant, called the Conversion Factor (CF), is a national adjustment factor, which is identical across specialties, areas, and procedures. The 2017 CF is equal to $35.8887. The GAFs are a proxy for cost of living, adjusting for differences in input costs across payment regions.

The RUC's recommendations across the years have been constantly widening the gap between the procedure reimbursements usually carried out by specialists and those regularly carried out by primary care.

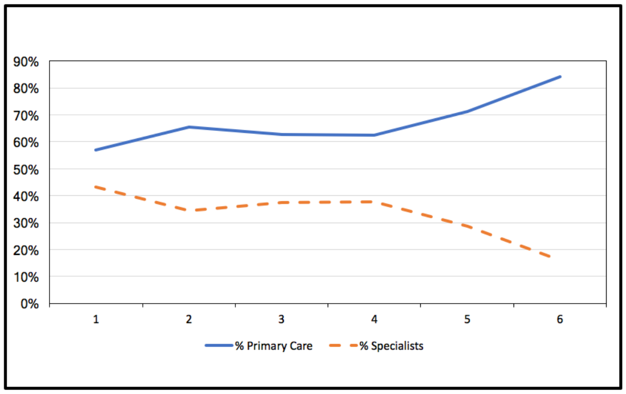
Since the reimbursement does not depend on who carries out the procedure, but only on the procedure itself, and specialist procedures are more highly priced than typical primary care procedures, this payment system generates financial incentives for primary care doctors to substitute to more specialized, remunerative procedures when possible. See the next section for some data analysis that was present in Chapter 2 and reported here again for convenience, supporting this statement.

3.4.3 Physicians in Different Locations Act Differently

This subsection briefly summarizes some data findings available in Chapter 2, which support the hypothesis held in this chapter that physicians take into consideration the level of reimbursement in their decision-making. Since physicians perform different procedures in different places, the choice of location inherently encompasses that information.

In particular, primary care physicians are able to perform more remunerative specialist procedures in rural areas, where specialists are not as present. Since specialist procedures have been paid increasingly more over the years, the possibility of carrying such procedures out in more rural areas makes rural areas more attractive from a remuneration point of you. However, classical analysis only considers a tradeoff between wages and amenities, and does not take into consideration this other very important remuneration channel.

I report here some data evidence on physicians acting differently along the urbanity index. In first need to identify what constitutes a specialist procedure. To do so, I look at the number of services per procedure carried out by each doctor and see how many doctors in primary care perform it and how many specialists perform it over the entire dataset. Then, for each procedure, I calculate the percentage of services performed by primary care physicians (PC) versus specialists. I then consider the procedures of interest to be those performed by specialists 50-80% of the time and by the primary care the remaining 20-50%. Robustness checks show that the results are robust independently of the range chosen, but their effect is stronger for tighter ranges. This approach creates a specialization index for each procedure, from 0 to 1. An index value equal to 0 means that the procedure is only carried out by specialists, while an index value of 1 means that it is always carried out by primary care. Therefore, the lower the index value, the more the procedure is a specialized one. Next, I consider all the procedures carried out by each doctor and their respective specialization index values. I then take the average of these values across all the procedures carried out by each doctor, for every doctor. This generates a physician-level specialization index which marks whether or not each doctor behaves as a specialist. Similarly to before, if a doctor had an average of 0, it would mean that he only carried



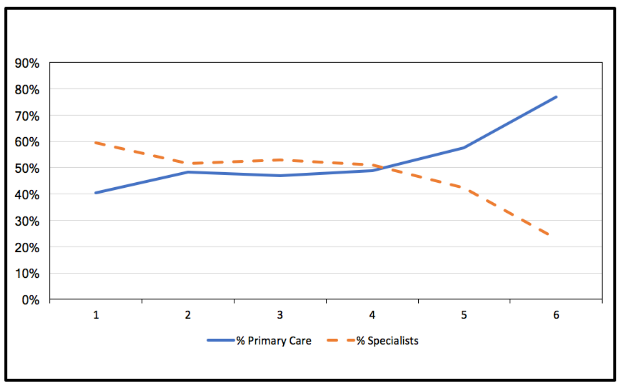
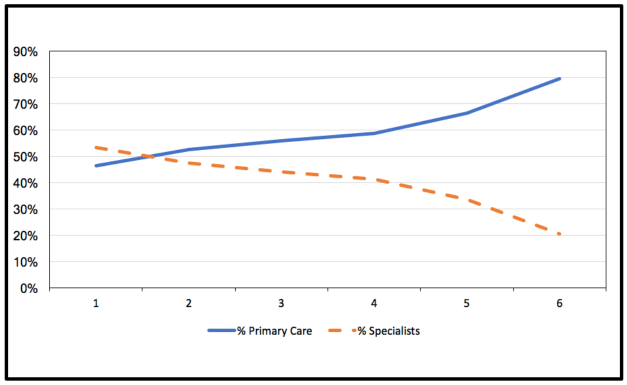


Figure 3.4: Procedures usually carried out by specialists 50-80% of the time

Notes: This figure concentrates on procedures usually carried out by specialists 50-80% of the time. The first figure looks at the percentage of doctors carrying out these procedures (even just once) who are in primary care vs some specialty, across urbanity levels. The second figure looks at the percentage of services provided by primary care vs some specialty, across urbanity levels. The urbanity of the area is an index from 1 to 6, where a higher value denotes a more rural area.

out specialist procedures and if he had an average of 1, it would mean that he only carried out PC procedures. Therefore, the lower the average, the higher the number of specialist procedures carried out by the doctor. I call this variable the degree of specialization of doctors. I then focus on procedures carried out by PC physicians 20-50% of the time and look at the distribution of doctors across the urbanity index, as shown in Figure 2.

I then restrict my attention to highly specialized procedures, i.e. the procedures carried out



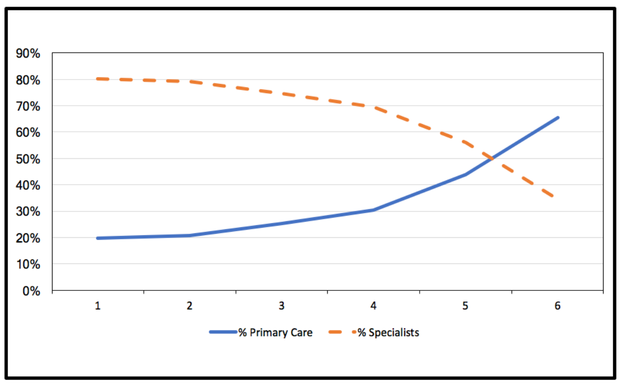


Figure 3.5: Procedures usually carried out by specialists 70-80% of the time

Notes: This figure concentrates on procedures usually carried out by specialists 70-80% of the time. The first figure looks at the percentage of doctors carrying out these procedures (even just once) who are in primary care vs some specialty, across urbanity levels. The second figure looks at the percentage of services provided by primary care vs some specialty, across urbanity levels. The urbanity of the area is an index from 1 to 6, where a higher value denotes a more rural area.

by specialists 70-80% of the time. I then analyze how many doctors and how many of these services are carried out by primary care doctors and by specialists across the urbanity level, and present the results in Figure 3.

This brief data analysis shows how primary care doctors take over more specialist procedures in rural places, and do so even more in locations where specialists are not around. The income differential between procedures typically carried out by primary care physicians and those typically carried out by specialists is key in this behavior and supports the hypothesis of this chapter that reimbursements should be included when analyzing physicians' location choice.

For a more complete analysis on physicians' response to the financial incentives generated by this behavior, refer to Chapter 2.

3.5 Model

From now on, for ease of exposition, I will refer to location choice, city choice, and hospital referral region (HRR) choice interchangeably. The goal of HRRs is to define areas that are self-contained markets for physicians, so that the majority of patients living in that area would be able to remain within their HRR for any visit they need. There are 306 HRRs in the United States. The model shown here is written as the model of a physician picking their location choice. The model is generalized in the obvious way in the estimation when I focus on first-job choices only, recalling that the change in the total population of physicians of either type is given by the population of new physicians of either type.

3.5.1 Physician Supply

I set up physicians' choice of a location as a structural static discrete choice location. Physicians pick a hospital referral region (HRR) to live in. The goal of HRRs is to define areas that are self-contained markets for primary care, so that the majority of patients living in that area go to primary care physicians within that area. Since physicians are picking the location of their job, HRRs provide me with the area that will constitute their market for medical procedures they will carry out. The outside choice is given by the HRRs that are not picked by them every year.

Physicians are grouped into two main specialty divides: primary care and specialty care. Individuals are heterogeneous along their specialty k and two demographic characteristics ℓ: the quality of the residency they completed as a proxy of their skill, q, and whether they are foreign, f. The quality of the residency attended is used as a proxy of the skill level of the physicians.

To approximate for the fact that higher-skilled residents have more options available to them than their lower-skilled counterparts, I rank both jobs and individuals by their ranking. The top 1% of physicians each year is the only group who has access to the top 1% jobs. Of course, they are also able to pick any job that is lower-ranked than they are. The top 10% physicians can pick any job that is equal or lower than their ranking. From the top 50% onward, physicians can pick jobs that are immediately above their ranking or below theirs. For example, a top 40% individual has all jobs that are below the 30% jobs in her choice set. It is important to recall that since, in the estimation, locations are available so long as jobs of the "correct" quality ranking are available within them, this assumption does not bite for most physicians of higher qualities, and matters only for lower-quality physicians.

Cities do not only differ by the wages and the physician-type mix. They differ by the level of amenities. I collect amenities on a variety of characteristics, grouped into seven main categories: cost of housing, entertainment, safety, transportation, education, crime, and environment. Amenities x_{jt} are treated as exogenous in this setting (physicians are one occupation only that will not influence the amenities in that location).

Finally, physicians display a preference for locations that are close to where they completed their residency. Therefore, preferences of workers with the same demographic characteristics ℓ for a HRR j can differ due to preferences to remain within the residency's HRR and state.

As commonly done in the literature, I express physicians' preferences as the indirect utility function physicians receive when picking HRR j in year t. I suppressed the time index t for ease of read. Residents pick a location within the whole nation, but they compete with the graduates that are also picking a location in the same year. Recall that residents are differentiated along their specialty group, their quality, and their foreign status.

I utilize the micro-data that I collected to let physicians differ in how they value the net income offered in different locations. The endogeneity issue that is commonly present within the mean utility parameters will then disappear, as compensation will not be contained in the mean utility anymore and there are no restrictions imposed between the unobserved amenities and the error term.

I let physicians differ in their preferences not only due to the location of their residency and the idiosyncratic shock, but also due to the net income they receive. Since I know the medical school physicians attended and I use this information to calculate the average payment of student loans, physicians actually differ in the net income they would receive in the same location. Therefore, the specification I run is the following:

$$\max_j u_{ij} = \overbrace{\beta^{k,\ell} x_j + \xi_j^{k,\ell}}^{\delta_j^{k,\ell}} + \overbrace{\alpha^{k,\ell} y_{ij} + \beta_j^{k,\ell} x_{ij}}^{\mu_{ij}} + \varepsilon_{ij} \tag{8}$$

where

$$u_{ij} = \begin{cases} \delta_j^{k,\ell} & \text{mean utility} \\ +\mu_{ij} & \text{stochastic coefficients} \\ +\varepsilon_{ij} & \text{iid T1EV error term} \end{cases} \tag{9}$$

where k represents the specialty group of the physician (primary care vs. specialty) and ℓ

represents the demographics of the physicians, namely their quality ranking q_i and their foreign status f_i. x_j are the location characteristics (the observed amenities), $\xi_j^{k,l}$ are location-year unobservables. y_{ij} is net income, which includes, as mentioned before: the expected wage income, the expected procedure revenue, the expected expenses (housing costs, malpractice insurance, student loans), and the expected subsidies (loan forgiveness affects the amount of student loans, while salary incentives increase the expected wage income). The ε_{ij} are drawn from Type 1 extreme value distribution and are independent and identically distributed across physicians, locations, and years.

Then, the probability that a physician i of type ℓ in specialty k picks location j in a given year is:

$$\hat{s}_{ijt} = \frac{\exp\left\{\delta_{jt}^{k,\ell} + \mu_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{k,\ell} + \mu_{imt}\right\}} \tag{10}$$

where M is equal to the number of HRRs.

The overall portion of doctors in specialty k picking location j in a given year across all demographic characteristics can be found by summing the individual market shares across the individuals within each type and across types. The number of primary care and specialty care physicians in j at time t are respectively:

$$N_{jt}^{PC} = \sum_{\ell \in q,f} \sum_{i=1}^{N_{\ell t}^{PC}} \frac{\exp\left\{\delta_{jt}^{PC,\ell} + \mu_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{PC,\ell} + \mu_{imt}\right\}} N_{\ell t}^{PC} \tag{11}$$

$$N_{jt}^{SP} = \sum_{\ell \in q,f} \sum_{i=1}^{N_{\ell t}^{SP}} \frac{\exp\left\{\delta_{jt}^{SP,\ell} + \mu_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{SP,\ell} + \mu_{imt}\right\}} N_{\ell t}^{SP} \tag{12}$$

Net income in the mean utility $\delta_{\mathbf{j}}^{\mathbf{k},\ell}$ The discrete-choice literature usually includes the monetary value in the mean utility (for example, the product price in discrete choice models for differentiated products). This is usually due the fact that the monetary value does not differ by the individual i, as it is the case, for example, with cereal, where the price does not differ by the purchaser. This same assumption has usually been kept in analyses where the monetary value indeed varies for each individual, as it is the case here. I use the micro data to calculate an average net income that would be available in a given location j for physicians of type ℓ in specialty k and estimate the model again. This average net income still includes all the elements present in the micro data (salary, reimbursements, housing cost, malpractice insurance, student loans), but it simply represents what the average net income is for a physician of type ℓ in specialty k in location j. I show in the results that the coefficients found do not differ much from those found letting net income vary for each individual. The correct measure of net income and the correct specification of the choice sets are the key to the results found in this chapter.

Physician i in specialty k and with demographic characteristics of type ℓ then solves:

$$\max_j u_{ij} = \overbrace{\alpha^{k,\ell} y_j + \beta^{k,\ell} x_j + \xi_j^{k,\ell}}^{\delta_j^{k,\ell}} + \overbrace{\beta_j^{k,\ell} x_{ij}}^{\mu_{ij}} + \varepsilon_{ij} \tag{13}$$

where (y_j, x_j) are now the location characteristics (net income as defined in Section 3.1 and amenities, respectively), while everything else follows exactly as above.

The Independence of Irrelevant Alternatives (IIA) Notice that the IIA property does not hold here. First, the individual preferences μ_{ij} allow for correlation in preferences within areas and within states due to physicians' preferences to have a preference to remain close to their residency. Within each area, preferences vary by specialty and by ℓ, therefore breaking the IIA property within each region.

3.5.2 Physician Demand

I model health firms in the city to use capital as well as a composition of primary care and specialty care workers, so that the composition of the two types in a city matters quite greatly for production. The reasoning for this is to imagine physicians as employed by clinics/hospitals/physician offices, which use machinery as capital and a given mix of primary care and specialty care physicians to produce a given health good, which I assume, for now, to be one and homogenous in production across the two types.

The productivity of primary care and specialty care physicians depends on the mix between the two types, due to the fact that the type of work carried out by primary care highly depends on whether or not specialty care is already carried out in a given location (Falcettoni 2017).[7] Physicians then receive a wage as well as fee-for-service reimbursements, the sum of which determines the total compensation. Reimbursements, and therefore compensation, depend on the specific procedures carried out. The wage endogenously responds to changes in physician employment, while reimbursements endogenously respond to the mix of types of physicians in the city. The wage is also impacted by the changes in the physician's productivity caused, once again, by the ratio between primary and specialty care physicians. Therefore, total compensation clearly responds to changes in the employment of either type of physicians. Physicians could also be self-employed. This set-up can easily include self-employment by imagining the physician to be simply employed in her own firm. Since I observe whether or not physicians are in an office or in a facility setting, I can easily allocate income correctly.

[7] Recall the discussion in Section 4 summarizing the main findings in Chapter 2 on physicians' procedures by specialty and area.

Each Hospital Referral Region j produces a medical good through a high number of homogenous firms (index suppressed) that employ primary care physicians (N_{jt}^{PC}) and specialists (N_{jt}^{SP}) and use machinery (capital K_{jt}). Production follows a Cobb-Douglas function where the total number of doctors employed (D_{jt}) follows a CES function:

$$
\begin{aligned}
M_{jt} &= D_{jt}^{\alpha} K_{jt}^{1-\alpha} && (14) \\
D_{jt} &= \left(\theta_{jt}^{PC}\left(N_{jt}^{PC}\right)^{\rho} + \theta_{jt}^{SP}\left(N_{jt}^{SP}\right)^{\rho}\right)^{\frac{1}{\rho}} && (15) \\
\theta_{jt}^{PC} &= f_{PC}\left(N_{jt}^{PC}, N_{jt}^{SP}\right)\exp\left(\varepsilon_{jt}^{PC}\right) && (16) \\
\theta_{jt}^{SP} &= f_{SP}\left(N_{jt}^{PC}, N_{jt}^{SP}\right)\exp\left(\varepsilon_{jt}^{SP}\right) && (17)
\end{aligned}
$$

which leads to the usual elasticity of substitution between primary care physicians and specialists of $\frac{1}{1-\rho}$. Notice This setup for physician demand is borrowed from the extensive literature on the wage differential between high- and low-skilled workers, such as Katz and Murphy (1992) and, more recently, Diamond (2015).

$\theta_{jt}^{k}\,\forall k = PC, SP$ is the productivity of primary care physicians and specialists. The two error terms are the exogenous factors that affect the productivity levels, while the function that takes into consideration the employment of either type of physicians endogenously affects the productivity of either type. This setup works well in my model since primary care physicians behave differently and can carry out different procedures when specialists are not around. Therefore, their productivity highly depends on the number of physicians of either type within a location. The two functions are not specified by a parametric form to not make strong assumptions on the way that the number of physicians directly impacts productivity.

Since the firms are perfectly competitive, they hire until total compensation is equal to the marginal product of labor. The capital market is assumed to be frictionless and national, so that firms can get capital at price p_t, equal across all locations. Finally, since firms are homogenous and the production function is Cobb-Douglas, the firm problem is representative to each location's physician demand. Solving the above problem and log-linearizing:

$$\begin{aligned}
\text{comp}_{jt}^{PC} &= a_t + (1-\rho)\,d_{jt} + (\rho-1)\,n_{jt}^{PC} + \log\left(f_{PC}\left(N_{jt}^{PC}, N_{jt}^{SP}\right)\right) + \varepsilon_{jt}^{PC} && (18)\\
\text{comp}_{jt}^{SP} &= a_t + (1-\rho)\,d_{jt} + (\rho-1)\,n_{jt}^{SP} + \log\left(f_{SP}\left(N_{jt}^{PC}, N_{jt}^{SP}\right)\right) + \varepsilon_{jt}^{SP} && (19)
\end{aligned}$$

$$D_{jt} = \left(f_{PC}\left(N_{jt}^{PC}, N_{jt}^{SP}\right)\exp\left(\varepsilon_{jt}^{PC}\right)\left(N_{jt}^{PC}\right)^{\rho} + f_{SP}\left(N_{jt}^{PC}, N_{jt}^{SP}\right)\exp\left(\varepsilon_{jt}^{SP}\right)\left(N_{jt}^{SP}\right)^{\rho}\right)^{\frac{1}{\rho}} \tag{20}$$

where lowercase letters stand for log-variables, comp is the logarithm of the total compensation physicians receive (salary and reimbursements) and a_t is a constant, given by: $a_t = \log\left(\alpha\left(\frac{(1-\alpha)}{p_t}\right)^{\frac{1-\alpha}{\alpha}}\right)$.

The physician demand equations can be approximated with log-linear aggregate physician demand, as commonly done in the labor literature:

$$\begin{aligned}
\text{comp}_{jt}^{PC} &= \beta_{0,pc} + \gamma_{pc}^{pc} n_{jt}^{PC} + \gamma_{sp}^{pc} n_{jt}^{SP} + \varepsilon_{jt}^{PC} && (21)\\
\text{comp}_{jt}^{SP} &= \beta_{0,sp} + \gamma_{pc}^{sp} n_{jt}^{PC} + \gamma_{sp}^{sp} n_{jt}^{SP} + \varepsilon_{jt}^{SP} && (22)
\end{aligned}$$

where the total compensation and employment in each j are data, while the errors are unobserved, and γ_{pc}^{pc}, γ_{sp}^{pc}, γ_{pc}^{sp}, γ_{sp}^{sp} are the parameters to be estimated.

3.5.3 Equilibrium

The equilibrium is given by a set of wages and quantity of physicians for every location j in every year t :

$\left(\text{comp}_{jt}^{PC*}, \text{comp}_{jt}^{SP*}, N_{jt}^{PC*}, N_{jt}^{SP*}\right)_{\forall j,t}$ such that:

1. Demand for primary care physicians equals supply of primary care physicians in each city:

$$\begin{cases} N_{jt}^{PC*} & = \sum_{\ell \in q,f} \sum_{i=1}^{N_{\ell t}^{PC}} \frac{\exp\left\{\delta_{jt}^{PC,\ell} + \mu_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{PC,\ell} + \mu_{imt}\right\}} N_{\ell t}^{PC} \\ \text{comp}_{jt}^{PC} & = \beta_{0,pc} + \gamma_{pc}^{pc} n_{jt}^{PC*} + \gamma_{sp}^{pc} n_{jt}^{SP} + \varepsilon_{jt}^{PC} \\ n_{jt}^{PC*} & = \log N_{jt}^{PC*} \end{cases} \tag{23}$$

2. Demand for specialists equals supply of specialists in each city:

$$\begin{cases} N_{jt}^{SP*} & = \sum_{\ell \in q,f} \sum_{i=1}^{N_{\ell t}^{SP}} \frac{\exp\left\{\delta_{jt}^{SP,\ell} + \mu_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{SP,\ell} + \mu_{imt}\right\}} N_{\ell t}^{SP} \\ \text{comp}_{jt}^{SP} & = \beta_{0,sp} + \gamma_{pc}^{sp} n_{jt}^{PC} + \gamma_{sp}^{sp} n_{jt}^{SP*} + \varepsilon_{jt}^{SP} \\ n_{jt}^{SP*} & = \log N_{jt}^{SP*} \end{cases} \tag{24}$$

3. The compensation clears the market:

$$\begin{cases} \text{comp}_{jt}^{PC*} & = \beta_{0,pc} + \gamma_{pc}^{pc} n_{jt}^{PC*} + \gamma_{sp}^{pc} n_{jt}^{SP*} + \varepsilon_{jt}^{PC} \\ \text{comp}_{jt}^{SP*} & = \beta_{0,sp} + \gamma_{pc}^{sp} n_{jt}^{PC*} + \gamma_{sp}^{sp} n_{jt}^{SP*} + \varepsilon_{jt}^{SP} \end{cases} \tag{25}$$

Recall that total compensation is contained in the $\delta_{jt}^{k,\ell}$'s as part of the net income received by physicians.

3.6 Estimation

3.6.1 Amenity Index

The computation of the amenity index follows Diamond (2015). The amenity index is meant to capture all the different amenity bundles available in different places. To approximate for such bundle as closely as possible, I include eight different categories: clothing stores, educational amenities, environment, health facilities, crime, transportation facilities, long commute, and traffic. Recall that job availability and the characteristics of the patients available are analyzed separately from this index.

Clothing stores per capita is calculated using the U.S. Census data on apparel stores; education includes the county spending per pupil up to secondary school as well as state spending per capita on libraries, primary, and secondary schools; environment includes the investment in parks and green spaces, the number of parks, the number of days marked with pollution, the median level of pollution, the number of good, moderate, and unhealthy days as measured by the EPA (using the air quality index); the health facility index includes investment in hospitals and health facilities; crime includes the number of correction facilities, violent crimes, murders, rapes, robberies, aggravated assaults, property crimes, burglaries, thefts, and motor thefts per capita; transportation facilities includes highways, airports, parkings, and harbors per capita; commute includes the percentage of people within the area commuting, by length of commute, from up to 14 minutes to over an hour; finally, traffic includes the percentage of people that commute by car, by length of commute, to proxy for the number of cars that would be in an area. I use principal component analysis (PCA) based on correlation (due to the different scales of the variables) to build the index. I extract the first component for each of the components of each index first, and I then run

PCA again on the individual categories mentioned above to generate the full amenity index.

Each individual index correctly puts the right weight on the single components. Environment puts negative weight on the days with pollution, the median level of pollution, moderate, and unhealthy days, correctly picking up that those factors decrease the quality of the air, while all other factors improve it. Long commute puts a negative weight on short commutes up to 24 minutes, with factor loadings increasing in the time of commute, correctly picking up that short commutes decrease the commute length, and more so, the shorter the commute. Traffic puts a negative weight on short commutes by car below 20 minutes, correctly picking up that areas in which people commute little by car to get to work are characterized by less traffic. All the other indices put positive weights on the different factors, correctly picking up that they each contribute to the index itself.

I finally run PCA again on the single indices to create the amenity index used in the chapter. The index for both specialty groups is presented in Table 3. The index is able to capture that crime, a long commute, and traffic are negative attributes of an area. It is also able to capture that, instead, a high number of stores, a high quality of the environment, and a high investment in education, health facilities, and transportation are all positive attributes of an area. To check that this is in fact correct, I rank the hospital referral regions according to the index level. The amenity index ranked HRRs inside and around New York, Chicago, DC, San Francisco, and Seattle all at the top of the list. Those cities are all places generally considered to have a high level of amenity, reinforcing the validity of the index.

3.6.2 Instrumental Variables

I use Bartik (1991) instruments to be able to identify my parameters of interest. Bartik shocks are generally defined as local labor demand shocks driven by the share of the city's

Table 3.8: Amenity Index

Variables	First Components, Primary Care	First Components, Specialists
Clothing Stores	0.0525	0.0578
Education	0.4828	0.4764
Environment	0.3529	0.3800
Health	0.4595	0.4716
Crime	-0.0201	-0.0273
Transportation	0.4550	0.4620
Long Commute to Work	-0.3257	-0.3038
Traffic	-0.3392	-0.3207

Notes: These results come from the estimation of the amenity index discussed in the chapter. Each value represents the first components obtained through principal component analysis (using correlation). First, I run principal component analysis on the single categories. Then I run principal component analysis again on the single categories to obtain the first components shown in this table, representing the weight of each category on the final index. More details are available in the text. The first components of each category are available in the online appendix.

employment in that industry with respect to the importance of that same industry nationally. Bartik instruments are therefore able to measure the change in a region's labor demand that is induced by changes in the national demand for different industries' products.

Following this logic, I will utilize my micro data on physicians' transactions at the procedure level for Medicare to be able to identify labor demand shocks that are uncorrelated with labor supply shocks. The identifying assumption in this setting is that labor demand is procedure-specific, while labor supply is not. In other words, for example, patients care about having someone carrying out an EKG, if they do not have it already, more than X-Rays, if someone already carries those out, but the physician herself, already assigned to a specialty, does not have a procedure-specific taste.

In order for this to hold, the rates I consider have to be exogenous, otherwise other issues of endogeneity could be present. The reason I utilize reimbursement rates is that reimbursement rates are set by policy. Reimbursement rates change for the whole nation according to the decisions made by the reimbursement committee. This allows me to evaluate the monetary impact of the productivity shocks on procedures through the shock on reimbursements:

$$B^{SP}_{jt,reimb} = \sum_{q\in treatments} \frac{N^{SP,q}_{j,t-k}}{\sum_{q'} N^{SP,q'}_{j,t-k}} \log\left(\frac{\sum_{m\neq j} reimb^{SP,q}_{m,t}}{\sum_{m\neq j} reimb^{SP,q}_{m,t-k}}\right) \tag{26}$$

$$B^{PC}_{jt,reimb} = \sum_{q\in treatments} \frac{N^{PC,q}_{j,t-k}}{\sum_{q'} N^{PC,q'}_{j,t-k}} \log\left(\frac{\sum_{m\neq j} reimb^{PC,q}_{m,t}}{\sum_{m\neq j} reimb^{PC,q}_{m,t-k}}\right) \tag{27}$$

which can be written in an equivalent way as:

$$B^{SP}_{jt,reimb} = \sum_{q\in treatments} \frac{N^{SP,q}_{j,t-k}}{N^{SP}_{j,t-k}} \left(\overline{reimb}^{SP,q}_{m\neq j,t} - \overline{reimb}^{SP,q}_{m\neq j,t-k}\right) \tag{28}$$

$$B^{PC}_{jt,reimb} = \sum_{q\in treatments} \frac{N^{PC,q}_{j,t-k}}{N^{PC}_{j,t-k}} \left(\overline{reimb}^{PC,q}_{m\neq j,t} - \overline{reimb}^{PC,q}_{m\neq j,t-k}\right) \tag{29}$$

where $\frac{N^{SP,q}_{j,t-k}}{N^{SP}_{j,t-k}}$ is the share of specialists carrying out procedure q at the beginning of the period in HRR i and $\frac{N^{PC,q}_{j,t-k}}{N^{PC}_{j,t-k}}$ is, equivalently, the share of primary care physicians carrying out procedure q in 2012 in HRR i, while $\left(\overline{reimb}^{SP,q}_{j\neq i,t} - \overline{reimb}^{SP,q}_{j\neq i,t-k}\right)$ is the growth in average reimbursement to specialists for procedure q between 2012 and 2016 in all other HRRs but HRR i, and $\left(\overline{reimb}^{PC,q}_{j\neq i,t} - \overline{reimb}^{PC,q}_{j\neq i,t-k}\right)$ is the equivalent measure for primary care physicians.

Instrument validity This instrument will be valid, relevant, and exogenous under the following restrictions:

1. There needs to be enough variation in the national growth rates across different procedures (i.e. $\left(\overline{reimb}^{SP,q}_{j\neq i,t} - \overline{reimb}^{SP,q}_{j\neq i,t-k}\right)$ and $\left(\overline{reimb}^{PC,q}_{j\neq i,t} - \overline{reimb}^{PC,q}_{j\neq i,t-k}\right)$ are different for different q).

This is easily respected because rate changes are set by policy and the reimbursement rates are different for different procedures, so there are enough changes across the 5 years considered for this to hold.

2. There needs to be enough variation in the share of physicians carrying out procedure q across areas j ($\frac{N^{SP,q}_{i,t-k}}{N^{SP}_{i,t-k}}$, $\frac{N^{PC,q}_{i,t-k}}{N^{PC}_{i,t-k}}$ are different for different i), or in other words, the mix of procedures carried out has to vary by location.

3. The exclusion restrictions have to be respected:

   (a) No procedure q is concentrated in one area only.

   (b) There is no supply effect or shock that drives the Bartik instrument.

Therefore, I need to test the key identifying assumption that there is enough variation in the procedure mix carried out in different places and that these differences in the procedure mix are uncorrelated with location unobservables. First, as shown in Figure 4, the instrument created displays high variation across and within urbanity types.

Second, the exogeneity of the instrument could be challenged thinking that differences in the procedure mix carried out by physicians are correlated with the same characteristics that make people decide to live in different locations. This is exactly why I exploit the changes in the policy reimbursement rates and the procedure count observed across the years in my data. Since the instrument is calculated using the time changes observed between 2012 and 2016, it is unlikely that unobserved location amenities are systematically correlated to these changes across time. Even though I run a two-step simultaneous GMM, I run

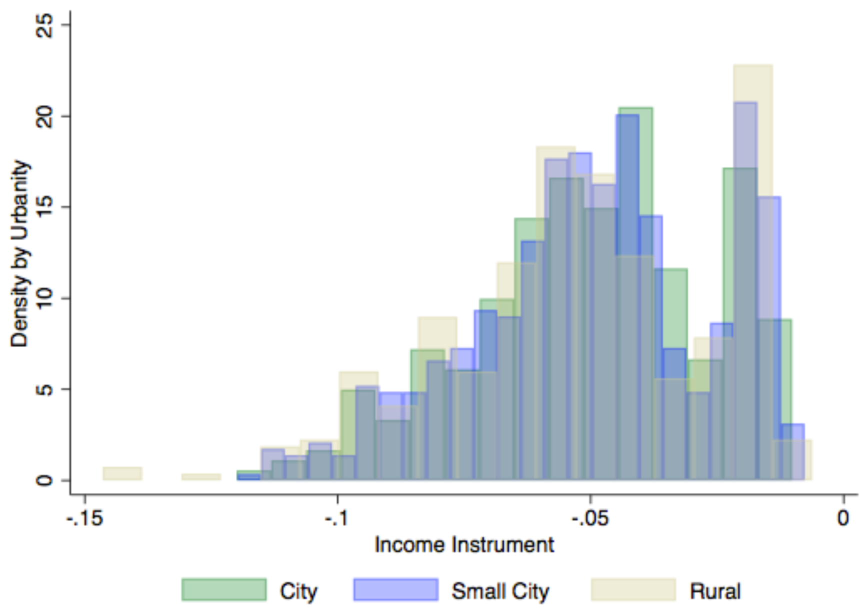


Figure 3.6: Income Instrument Density by Urbanity Index

Notes: This figure shows density distribution of the income instrument created, across and within urbanity types. Source: CMS.

a 2SLS estimation to get a feeling of the first-stage regression results and determine the instrument strength. The F-Stats are high (~68), suggesting that the instrument performs well in income prediction. The full estimation passes the overidentification Hansen's J-test as well, with a p-value equal to 0.4182 in the first case and 0.4049 in the other. The rule of thumb is that a high p-value indicates a good model fit, and a p-value that is not too high suggests that there are no other issues related to the model.

Finally, the Bartik demand shocks are unrelated to local city characteristics since they are built based on national shocks to the physicians' reimbursement level. Since I also interact them with malpractice insurance premia, notice that changes in the malpractice insurance premia do not depend on the attractiveness of the city, but vary substantially within and across locations. Simultaneous estimation guarantees identification thanks to the instruments' ability to affect all endogenous variables at the same time and simultaneously identify the parameters of interest.

3.6.3 Physician Supply

The estimation of physicians' preferences is a two-step estimation procedure, following BLP (1995). First, I use maximum likelihood to identify how much physicians of either type in each year want to live in each location, obtaining the mean utility level for each location $\left(\delta_j^{k,\ell}\right)$ and the individual coefficients (contained in μ_{ij}). Recall that in the estimation, $\beta_j^{k,\ell}$ is a vector of two parameters, representing the semi-elasticity of demand with respect to whether the location chosen is within the same state $\left(\beta_{state}^{k,\ell}\right)$ and area $\left(\beta_{HRR}^{k,\ell}\right)$ of residency. I then use these in the second step to estimate the trade-off physicians face between wages and other characteristics in their location choice through simultaneous equation non-linear GMM, using moments on physicians' preferences and physician's demand. Standard errors are clustered by hospital referral region.

Maximum likelihood estimation to recover $\delta_{\mathbf{jt}}^{\mathbf{k},\ell}$, $\alpha^{\mathbf{k},\ell}$, $\beta_{\mathbf{j}}^{\mathbf{k},\ell}$

Let $\mathbb{I}_{ij}$ be a dummy variable that takes value one if physician i chooses location j. Recall that the probability that a physician i of type ℓ in specialty k picks location j in a given year is:

$$\hat{s}_{ijt}^{k,\ell} = \frac{\exp\left\{\delta_{jt}^{k,\ell} + \alpha^{k,\ell} y_{ijt} + \beta_j^{k,\ell} x_{ijt} + \varepsilon_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{k,\ell} + \alpha^{k,\ell} y_{imt} + \beta_m^{k,\ell} x_{imt} + \varepsilon_{imt}\right\}} \tag{30}$$

Recall that the same apparent "compensation offer" in a location is perceived differently by different individuals, as they each carry their level of student loans and expenses. By utilizing the micro-data, the net income variable is calculated for each individual exactly. Through this methodology, individuals of the same type ℓ are still allowed to differ in their preferences for locations according to the total net income that they individually would face in each location. The log-likelihood function is then given by:

$$\mathscr{L}^{k,\ell}\left(\delta_{jt}^{k,\ell},\beta_j^{k,\ell}\right)=\frac{1}{N_\ell^k}\sum_{i=1}^{N_\ell^k}\sum_{j=1}^{J}\mathbb{I}_{ij}\log\left(\hat{s}_{ijt}^{k,\ell}\left(\delta_{jt}^{k,\ell},\beta_j^{k,\ell};y_{ij},x_{ij}\right)\right) \tag{31}$$

This log-likelihood cannot be estimated directly because it would require a search over $J+1$ parameters (which is problematic, since J>300). Therefore, I instead use the BLP (1995) contraction that finds the parameters of interest by matching the observed shares in the data $s_{jt}^{k,\ell}$ to the estimated shares $\hat{s}_{ijt}^{k,\ell}\left(\delta_{jt}^{k,\ell},\beta_j^{k,\ell}\right)$:

$$T\left(\delta_j^{k,\ell}\right)=\delta_j^{k,\ell}+[\log\left(s_j^{k,\ell}\right)-\log\left(\hat{s}_j^{k,\ell}\left(\delta_j^{k,\ell},\beta_j^{k,\ell}\right)\right) \tag{32}$$

which reduces the estimation considerably, since for every $\beta_j^{k,\ell}$, there exists a unique $\delta_j^{k,\ell}=\left(\delta_1^{k,\ell},...,\delta_J^{k,\ell}\right)$ that matches the observed and estimated shares. The log-likelihood is then given by:

$$\mathscr{L}^{k,\ell}\left(\delta^{k,\ell}\left(\beta_j^{k,\ell}\right),\beta_j^{k,\ell}\right)=\frac{1}{N_\ell^k}\sum_{i=1}^{N_\ell^k}\sum_{j=1}^{J}\mathbb{I}_{ij}\log\left(\hat{s}_{ijt}^{k,\ell}\left(\delta^{k,\ell}\left(\beta_j^{k,\ell}\right),\beta_j^{k,\ell};y_{ij},x_{ij}\right)\right) \tag{33}$$

The recovered $\delta_j^{k,\ell}$ are now simply given by the amenities of a location, i.e. the common component of the utility that individuals within each type agree upon. The second stage then allows me to recover $\xi_{jt}^{k,\ell}$.

Net income in the mean utility $\delta_{\mathbf{j}}^{\mathbf{k},\ell}$ Here, I briefly show what varies in the estimation procedure if I allow for an average compensation by location that is invariant at the individual level.

First step: maximum likelihood estimation to recover $\delta_{\mathbf{jt}}^{\mathbf{k},\ell},\beta_{\mathbf{j}}^{\mathbf{k},\ell}$

Let $\mathbb{I}_{ij}$ be a dummy variable that takes value one if physician i chooses location j. Recall that the probability that a physician i of type ℓ in specialty k picks location j in a given year is:

$$\hat{s}_{ijt}^{k,\ell} = \frac{\exp\left\{\delta_{jt}^{k,\ell} + \beta_j^{k,\ell} x_{ijt} + \varepsilon_{ijt}\right\}}{\sum_{m=1}^{M} \exp\left\{\delta_{mt}^{k,\ell} + \beta_m^{k,\ell} x_{imt} + \varepsilon_{imt}\right\}} \tag{34}$$

The discussion above on the log-likelihood remains valid here, therefore I use the contraction mapping from BLP (1995) as above, so that for every $\beta_j^{k,\ell}$, there exists a unique $\delta_j^{k,\ell} = \left(\delta_1^{k,\ell}, ..., \delta_J^{k,\ell}\right)$ that matches the observed and estimated shares. The log-likelihood is then given by:

$$\mathscr{L}^{k,\ell}\left(\delta^{k,\ell}\left(\beta_j^{k,\ell}\right), \beta_j^{k,\ell}\right) = \frac{1}{N_\ell^k} \sum_{i=1}^{N_\ell^k} \sum_{j=1}^{J} \mathbb{I}_{ij} \log\left(\hat{s}_{ijt}^{k,\ell}\left(\delta^{k,\ell}\left(\beta_j^{k,\ell}\right), \beta_j^{k,\ell}; x_{ij}\right)\right) \tag{35}$$

Second step: two-step GMM to recover $\alpha^{\mathbf{k},\ell}$, $\beta^{\mathbf{k},\ell}$, $\xi_{\mathbf{j}}^{\mathbf{k},\ell}$

Now that both $\beta_j^{k,\ell}$ and $\delta_j^{k,\ell} = \left(\delta_1^{k,\ell}, ..., \delta_J^{k,\ell}\right)$ are recovered, all that is left to be estimated are the parameters on the net income $\alpha^{k,\ell}$ and on the amenities $\beta^{k,\ell}$.

The key issue in this part of the estimation is the endogeneity caused by the unobserved amenities ξ_j. While I include many amenities in the amenity index I discussed in Section 6.1, there could be other unobserved amenities that still impact physicians' choices. One such example is the fact that physicians might pick places surrounded by people that are similar to them. Due to the fact that physicians are paid more where amenities are fewer and that reimbursements vary geographically due to the discussion in Chapter 2 summarized in Section 3.1, the correlation between net income and unobserved amenities is strictly negative, i.e.

$$\mathbb{E}\left[y_j \xi_j^{k,\ell}\right] < 0 \tag{36}$$

This would bias $\alpha^{k,\ell}$ downward, as it can easily be verified by running a simple OLS regression, which estimates negative coefficients on income.

I utilize the income instrument discussed in Section 6.2 to address this issue. The identifying assumption is that there is enough variation in the procedure mix carried out in different places and that these differences in the procedure mix are uncorrelated with location unobservables. In formal notation:

$$\mathbb{E}\left[B^k_{jt,reimb}\xi^{k,\ell}_j\right] = 0 \tag{37}$$

3.6.4 Physician Demand

Recall the labor demand equations:

$$\begin{aligned}
\text{comp}^{PC}_{jt} &= \beta_{0,pc} + \gamma^{pc}_{pc} n^{PC}_{jt} + \gamma^{pc}_{sp} n^{SP}_{jt} + \varepsilon^{PC}_{jt} && (38)\\
\text{comp}^{SP}_{jt} &= \beta_{0,sp} + \gamma^{sp}_{pc} n^{PC}_{jt} + \gamma^{sp}_{sp} n^{SP}_{jt} + \varepsilon^{SP}_{jt} && (39)
\end{aligned}$$

and take the difference of the variables from the base values in 2012, utilizing the panel dimension of the data:

$$\begin{aligned}
\Delta\text{comp}^{PC}_{jt} &= \gamma^{pc}_{pc} \Delta n^{PC}_{jt} + \gamma^{pc}_{sp} \Delta n^{SP}_{jt} + \Delta\varepsilon^{PC}_{jt} && (40)\\
\Delta\text{comp}^{SP}_{jt} &= \gamma^{sp}_{pc} \Delta n^{PC}_{jt} + \gamma^{sp}_{sp} \Delta n^{SP}_{jt} + \Delta\varepsilon^{SP}_{jt} && (41)
\end{aligned}$$

As mentioned before, $\Delta\varepsilon^{PC}_{jt}$ and $\Delta\varepsilon^{SP}_{jt}$ represent the exogenous changes in the wages (the exogenous productivity changes). Since, by definition, the Bartik instruments above are demand shifters, I can write:

$$\begin{cases} \Delta\varepsilon_{jt}^{PC} & = \gamma_{pc}^{pc,inst} B_{jt,reimb}^{PC} + \gamma_{sp}^{pc,inst} B_{jt,reimb}^{SP} + \Delta\eta_{jt}^{PC} \\ \Delta\varepsilon_{jt}^{SP} & = \gamma_{pc}^{sp,inst} B_{jt,reimb}^{PC} + \gamma_{sp}^{sp,inst} B_{jt,reimb}^{SP} + \Delta\eta_{jt}^{SP} \end{cases} \tag{42}$$

where $\Delta\eta_{jt}^{PC}$ and $\Delta\eta_{jt}^{SP}$ are unobserved changes in the productivity change which are, by construction, uncorrelated with the demand shocks captured by the Bartik instruments. I can then redefine the labor demand equations as:

$$\begin{cases} \Delta\text{comp}_{jt}^{PC} & = \gamma_{pc}^{pc} pc_{jt} + \gamma_{sp}^{pc} sp_{jt} + \gamma_{pc}^{pc,inst} \Delta B_{jt,reimb}^{PC} + \gamma_{sp}^{pc,inst} \Delta B_{jt,reimb}^{SP} + \Delta\eta_{jt}^{PC} \\ \Delta\text{comp}_{jt}^{SP} & = \gamma_{pc}^{sp} pc_{jt} + \gamma_{sp}^{sp} sp_{jt} + \gamma_{pc}^{sp,inst} \Delta B_{jt,reimb}^{PC} + \gamma_{sp}^{sp,inst} \Delta B_{jt,reimb}^{SP} + \Delta\eta_{jt}^{SP} \end{cases} \tag{43}$$

where, as before, the physician demand elasticities $\gamma_i^k \forall i,k = pc,sp$ are the parameters of interest. These are identified using changes in physician supply which are not correlated with $\Delta\eta_{jt}^{PC}$ and $\Delta\eta_{jt}^{SP}$. I will use the interaction of the Bartik instruments (which are uncorrelated with $\Delta\eta_{jt}^{PC}$ and $\Delta\eta_{jt}^{SP}$ by construction) with region-based malpractice insurance reimbursement units. The malpractice units, also set by Medicare, are set by procedure and location, based on observed malpractice insurance premia, and they therefore proxy for the total malpractice insurance cost paid by physicians. The location adjustments, called geographical practice cost indices, which are set differently for work units and reimbursement units, react to the increase in the cost of life of the location. Now, take two cities with the same increase in physician demand, but that experience different changes in the total malpractice insurance costs. The city that experiences the higher cost increase will be less desirable to physicians, at an equal demand. This analysis will remain valid as long as the exclusion restrictions remain respected:

$$\mathbb{E}\left(\Delta\eta_{jt}^{PC}\Delta Z_{jt}\right) = 0 \quad (44)$$

$$\mathbb{E}\left(\Delta\eta_{jt}^{SP}\Delta Z_{jt}\right) = 0 \quad (45)$$

where $\Delta Z_{jt} \in \left\{\Delta B^{k}_{jt,reimb}\Delta MPGPCI_{jt}, \Delta B^{k}_{jt,reimb}\Delta MP^{k'}_{jt}\,\forall k,k' = pc,sp\right\}$. Once again, recall that

$$\mathbb{E}\left(\Delta\eta_{jt}^{PC}\Delta B^{PC}_{jt,reimb}\right) = 0 \quad (46)$$

$$\mathbb{E}\left(\Delta\eta_{jt}^{SP}\Delta B^{SP}_{jt,reimb}\right) = 0 \quad (47)$$

by construction.

Recall that all parameters of the demand model are estimated jointly with the supply parameters in the second step described above.

3.7 Results

3.7.1 Physician Supply

Table 4 presents the results for physicians' preferences in their choice of location, both for primary care (first panel) and specialists (second panel). In general, physicians like higher net incomes and higher amenities. Top-50 coefficients are generally noisier and indicate small differences. Top-50 primary care physician residents are more likely to be retained in the same state as residency, unlike specialty residents. Residents in all specialties are less likely to be retained in the same area as residency if they are from a top residency. Specialists are more elastic to income than primary care physicians. Top-50 residents are less elastic to income, even though the estimate is quite small. Overall, the elasticities

Table 3.9: Physician Supply: Individual Preferences ($\beta^{k,\ell}$, $\alpha^{k,\ell}$, $\beta^{k,\ell}_{state}$, $\beta^{k,\ell}_{HRR}$)

	Amenities		Amenities, Top 50		Amenities, Foreign	
	PC	SP	PC	SP	PC	SP
$\beta^{k,\ell}$	0.39	0.59	0.20	0.25	0.01	0.04
	(0.018)	(0.020)	(0.014)	(0.012)	(0.008)	(0.006)
	Income		**Income, Top 50**		**Income, Foreign**	
	PC	SP	PC	SP	PC	SP
$\alpha^{k,\ell}$	0.03	0.15	-0.005	-0.023	-0.001	0.001
	(1.18e-06)	(7.57e-06)	(2.58e-06)	(1e-05)	(0.001)	(0.001)
	State		**State, Top 50**			
	PC	SP	PC	SP		
$\beta^{k,\ell}_{state}$	2.77	1.75	0.42	-0.38		
	(0.012)	(0.035)	(0.018)	(0.053)		
	HRR		**HRR, Top 50**			
	PC	SP	PC	SP		
$\beta^{k,\ell}_{HRR}$	2.35	2.57	-1.48	-0.29		
	(0.005)	(0.042)	(0.008)	(0.063)		

Notes: These results come from the second specification of the physician supply analysis described in the chapter. Magnitude of the α represents the elasticity of demand of a location with respect to income. Magnitude of the state and HRR coefficients represent the semielasticity of demand with respect to whether the choice is within the same state or area (HRR) of residency, respectively. The coefficients are obtained through maximum likelihood estimation of the conditional logit model based on individual-level data on residency and choice locations. The sample includes all residents finishing residency, by specialty, between 2012 and 2016. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas.

displayed are very small, confirming that small monetary efforts such as those executed up to now to bring doctors to rural areas cannot be effective.

As mentioned beforehand, this estimation allows me to recover the unobserved amenities from the contraction mapping. The density distribution of the recovered unobserved amenities is shown in Figure 5. As expected, cities have higher unobserved amenities than rural

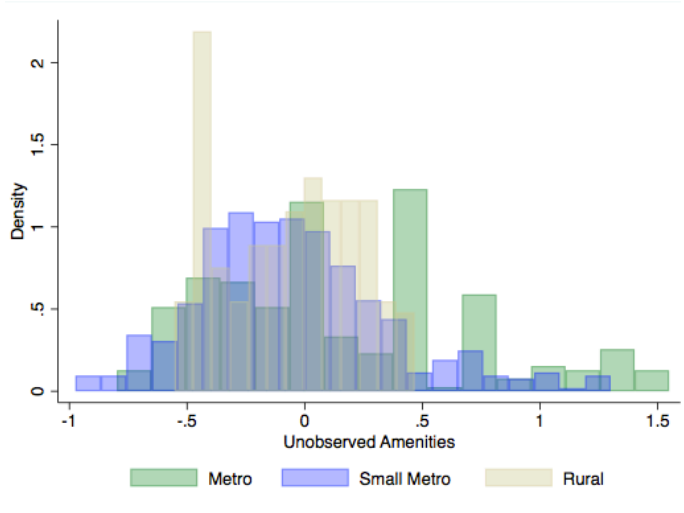


Figure 3.7: Density of Amenities, by Location Type

Notes: This figure shows the density distribution of the amenities implied by the model (both observed and unobserved), by location type. As expected, cities have higher amenity levels than rural areas.

places.

Preference for Retention Table 4 also reports the results for physicians' preferences for retention. Physicians display a preference for locations that are close to where they completed their residency. Therefore, preferences of workers with the same demographic characteristics k, ℓ for a HRR j can differ due to preferences to remain within the residency's HRR and state. This is motivated by two facts in the health literature: first, many physicians that want to return to their state of birth tend to pick a residency that already fulfills their preference, so this preference also proxies for a preference to return to the birthplace; secondly, many medical students initiate personal relationships during residency that lead to their choice of remaining close to their residency location (often due to the fact that their spouse is not in the medical profession, for example). These two facts lead to a third, widely discussed fact: many states display high rates of residency retention, with 54% of all residents in the US remaining within their state of residency for their first job. My data sample replicates this fact, with 51.4% of doctors picking to remain within the same state of residency.

Table 4 shows the estimates from the maximum likelihood estimation of the conditional logit model displaying the semi-elasticity of demand with respect to whether or not the choice is within the same state of residency first, and within the same hospital referral region after. I find that primary care physicians are about 3.8 times more likely to work in the same state as their residency and about 3.4 times more likely to work in the same hospital referral region as their residency. Similarly, specialists are 2.8 times more likely to work in the same state as their residency and about 3.6 times more likely to remain in the same hospital referral region for work. I am able to reject that retention values can be the same between primary care physicians and specialists. The appendix reports the semi-elasticity of retention estimates on a year-by-year basis.

I compare the base estimates with those of individuals that attended a top-50 residency. I find that top-50 residents in primary care are 0.4 times more likely to remain in the same state as their residency for work, but they are 1.5 times less likely to remain in the same area as residency. On the other hand, I find that top-50 residents in specialty care are 0.3-0.4 times less likely to be retained within the same state and area of residency.

This preference for retention agrees with the previous survey literature on physicians' choice of location (including, but not limited to, Cooper 1975), supporting and strengthening the literature's survey findings.

Comparing these results to the labor literature, I find a very interesting result. While all physicians are clearly high-skilled workers, primary care physicians display the same preference of retention as unskilled workers. Diamond (2015), for example, reports a base semi-elasticity of college of workers of being retained in their state of birth of about 2.6. That estimate is closer to the values I find for specialists, but much lower than the values that I find for primary care physicians. This shows that there are extremely important differences not only across occupation types, but also within occupations that might be ignored in current analyses.

Net income in the mean utility $\delta_{\mathbf{j}}^{\mathbf{k},\ell}$

As mentioned earlier in the text, I also run the model again using the micro data to calculate the average income that a physician would receive in a given location to compare it to the existing literature. I then run two different specifications of the model in which net income is a component of the mean utility. First, I assume that the demand elasticities are only a function of the elasticity of labor substitution between primary care physicians and specialists (Model 1). In the second specification, I relax this assumption and I let compensation respond to the employment of either type of physician (Model 2). The results are shown to be robust, indicating that a comprehensive measure of income is the main driver for the results.

Table 5 presents the results for physicians' preferences in their choice of location, both for primary care (first panel) and specialists (second panel). In general, physicians like higher net incomes and higher amenities. Top-50 residents are more elastic to both, while I do not observe significant differences between American and foreign physicians. Specialists are more elastic than primary care physicians with respect to both factors. As mentioned beforehand, the two specifications in Table 5 only vary on the demand side. I find that the elasticity that primary care physicians display is very similar in both cases. Specialists' elasticity to income is about double the elasticity found when the coefficient is estimated using the individual-level data. I find that primary care physicians are about 3.7 times more likely to pick a job within the same state of residency and about 3.4 times more likely to pick a job within the same hospital referral region as the residency. On the other hand, specialists are 3 times more likely to pick a job within the same state as residency and about 2.8 times more likely to pick a job within the same hospital referral region. I am able to reject that retention values can be the same between primary care physicians and specialists. The appendix reports the semi-elasticity of retention estimates on a year-by-year basis.

I compare the base estimates with those of individuals that attended a top-50 residency. These last estimates seem to be more noisy. I cannot conclude that top-50 primary care residents have a different value to remain within the same area of residency, but top-50 primary care residents have a lower value to remain within the same state. Top-50 specialty residents display a lower value of retention, and they are about 0.3-0.4 times less likely to be retained at the hospital referral region- and state-level.

3.7.2 Physician Demand

Table 6 presents the parameter estimates for physician demand. The estimated elasticity of labor substitution is quite high, equal to 1.01. The other specification allows for not only the labor substitution between the two types of physicians, but also for the effect of varying the employment of either type of physician. I observe a negative own-elasticity of primary care physicians' wages, but a positive own-elasticity of specialists' wages, suggesting that the specialists "feed off each other."

Finally, I observe a negative elasticity of specialists' wages with respect to primary care employment, as suggested by my discussion in Chapter 2.

3.8 Counterfactuals

Policymakers have historically used different monetary incentives to attract doctors to rural areas, most notably loan forgiveness and bonus incentives. The average sign-up bonus for

Table 3.10: Physician Supply: Income in the Mean Utility ($\delta_{j\ \ t}^{k,\ell}$)

	(1 - Base)		(1 - Top 50)		(1 - Foreign)	
	PC	SP	PC	SP	PC	SP
Compensation	0.043	0.074	0.019	0.020	-0.001	0.001
	(0.002)	(0.003)	(0.001)	(0.001)	(0.001)	(0.001)
Amenities	0.39	0.59	0.20	0.25	0.01	0.04
	(0.018)	(0.020)	(0.014)	(0.012)	(0.008)	(0.006)
Hansen's J stat	172.23					
p-value	0.3339					
	(2 - Base)		(2 - Top 50)		(2 - Foreign)	
	PC	SP	PC	SP	PC	SP
Compensation	0.036	0.065	0.016	0.015	-0.0004	-0.001
	(0.002)	(0.003)	(0.002)	(0.001)	(0.0005)	(0.001)
Amenities	0.49	0.73	0.24	0.29	0.001	0.047
	(0.019)	(0.026)	(0.014)	(0.013)	(0.006)	(0.006)
$\beta_{state}^{k,\ell}$	2.71	2.01	-0.35	-0.23		
	(0.041)	(0.037)	(0.069)	(0.050)		
$\beta_{HRR}^{k,\ell}$	2.40	1.79	-0.08	-0.36		
	(0.046)	(0.041)	(0.079)	(0.058)		
Hansen's J stat	143.95					
p-value	0.462					

Notes: These results come from the physician supply analysis described in the chapter. Magnitude of all rows but the last two represents the elasticity of the mean utility to each variable, by specialty group. Magnitude of the last two rows represents the semielasticity of demand with respect to whether the choice is within the same state or area (HRR) of residency, respectively. The coefficients on individual preferences and the mean utility levels are obtained through maximum likelihood estimation of the conditional logit model based on individual-level data on residency and choice locations. The coefficients on the mean utility are obtained through two-step generalized method of moments. The coefficients for top-50 and foreign residents are the differential effects of residents that graduated from a top-50 place and from being foreign with respect to the base coefficients. The sample includes all residents finishing residency, by specialty, between 2012 and 2016. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas. Compensation is net income defined as revenues coming from salary and reimbursements minus the expenses coming from malpractice insurance, rent, and student loan repayment. Health professional shortage areas that offer loan forgiveness exclude student loan repayment. I also let the individual preference parameters vary by year in a robustness check. The results from this estimation are available in the appendix.

Table 3.11: Physician Demand

	(1)	(2)
ρ	1.01	
	(0.004)	
γ_{pc}^{pc}		-0.55
		(0.06)
γ_{sp}^{pc}		0.51
		(0.05)
γ_{sp}^{sp}		0.16
		(0.05)
γ_{pc}^{sp}		-0.19
		(0.05)

Notes: These results come from the physician demand analysis described in the chapter. ρ represents the elasticity of labor substitution between primary care physicians and specialists in specifications (1) and (2) in the model. All γs represent the reduced-form coefficient determining the relationship between the employment of either type of physicians and their wages. All coefficients from the physician demand analysis are jointly estimated with the physician supply parameters of the main utility through two-step GMM.

a doctor to practice in rural areas has been estimated to be around $7,500.

I run three different counterfactuals under this setup: I evaluate the effect of current policies compared to no incentives, I evaluate the effect of a policy that switches the focus from loan forgiveness to salary incentives, and I evaluate the effect of a policy that only targets primary care physicians through salary incentives.

First, I estimate that loan forgiveness alone has increased the number of new primary care physicians choosing rural areas by 0.5% and of new specialists by 1.3%. Since loan forgiveness is particularly attractive to those students with high loans, a resorting effect happens, where residents re-maximize their utility and pick rural areas when their loans are the greatest, while those with lower loans move to the city as amenities offer a higher utility. To illustrate, Table 7 shows the percentage change in the primary care physician population with respect to the base case of no loan forgiveness in any area.

Table 3.12: Counterfactual Effect, by Specialty Group

	PC	SP
Loan Forgiveness	0.7%	1.3%
Salary Incentives	0.2%	0.1%

Notes: The table reports the percentage changes in physician population, by specialty type. "Loan Forgiveness" only includes the effect of a loan forgiveness policy, "Salary Incentives" includes the additional effect of a $7,500 salary incentives.

Second, I add a $7,500s bonus value in income by choosing rural areas. This effect adds another 0.2% with respect to the primary care population and an another 0.1% with respect to the specialist population in the world with only loan forgiveness. To illustrate again, the counterfactual percentage change in the primary care physician population with respect to the case of loan forgiveness only is also shown in Table 7.

These two exercises have replicated the effect of currently implemented policies. Regardless of specialty, the two current policies have led to a 1.2% increase in the number of physicians picking rural areas. Results suggest that specialists respond the most to current policies, which is mainly driven by the focus on loan forgiveness and the very high loans faced by specialists. However, the infrastructure necessary for specialists to operate greatly limits the opportunities for policy intervention, at least in the short-term.

The detailed information fed into my model allows me to also analyze the average quality level of the physicians who are incentivized by these policies. I find that while loan forgiveness might appear as an attractive option to bring physicians to rural areas, the physicians attracted there are in the bottom 25% of the quality ladder. This is mainly due to the fact that the physicians who are most responsive to loan forgiveness are those with very high debt. While attending top medical schools often leads to high student loans, it also gives physicians access to top residencies and, subsequently, to the most remunerative jobs. On the other hand, private low-ranked medical schools also lead to high student debt, but they are often followed by low-ranked residencies and low-quality jobs. Physicians who face this situation then find themselves with high debt and low-quality job perspectives, which incentivizes them to accept loan forgiveness whenever possible.

Given this, I run the experiment of using the US spending currently spent on medical student loan forgiveness to increase the salary incentives offered for rural area employment across all physicians. The evaluation of current and alternative policies is presented in Table 8. While this experiment maintains the same level of spending, salary incentives incentivize all physicians equally, not just those with high loans. US spending on loan forgiveness is between \$350 million and \$400 million. The redistribution of this spending as rural salary incentives across all physicians leads to an extra bonus of roughly \$35,000 for each physician picking rural areas. I find that such a policy would lead to almost 6 times more primary care physicians picking rural areas. Since primary care physicians are the main physician category that currently provides medical care to rural areas, and since they do not need a particular infrastructure to do so, these results suggest that policymakers should retarget spending from loan forgiveness to salary incentives and that offering salary incentives to primary care physicians only would be even more effective. The switch to salary incentives also allows for a more varied pool of physicians in terms of quality ranking, increasing the overall average quality of physicians.

Finally, I run the same exercise of switching to salary incentives, but targeting primary care physicians only. The increase in the primary care physician population is now substantial, while a few specialists are lost compared to the “no incentives” world, due to the increased competition coming from the rising primary care population.

These exercises served as an example to show how monetary incentives are currently not

Table 3.13: Impact of Current and Alternative Policies, by Specialty Group

Policy Environment	PC	SP
Data: New Rural Physicians	1,039	1,060
Model		
Current Policies	1,039	1,060
Remove All Incentives	971	773
Effect of Current Policies	+68	+287
Effect of Alternative Policy 1 - Target All	+407	+132
Effect of Alternative Policy 2 - Target Primary Care Only	+1,029	-22

Notes: The table reports the impact of current and alternative policies on the physician population, by specialty type.

strong enough for physicians to move to rural areas. They also suggest that policies aimed at the retargeting of spending from loan forgiveness to salary incentives would lead to almost 6 times more primary care physicians choosing rural areas. Finally, the pool of physicians attracted would be of a better quality on average under salary incentives compared to current policies.

3.9 Conclusion

This chapter used a combination of detailed and novel data to be able to assess the main factors affecting physicians' choice of location of their first job following residency.

This chapter overall suggested a few interesting results. Firstly, the results suggest that physicians respond positively to compensation and amenities, as theory would suggest. However, physicians do not respond much to monetary incentives. Specialists are more elastic than primary care physicians and respond more to both higher compensation and higher amenities. Nevertheless, none of the characteristics matter as much as the location of their residency. Retention is key, and those retained from medical school have an extremely low chance of moving away after residency. Thirdly, primary care physicians display the same preference of retention as unskilled workers in the labor literature, suggesting that specialists and primary care physicians are inherently different.

These results have great potential implications for policy-making: first, the results suggest that short-term policies should focus on physicians respond to other factors more than to compensation. The key mechanism to bring physicians to rural placements seems to be a very clear one: residencies need to be made available, offered, and maintained rurally. Not only it is much easier to retain than to attract physicians to a new location, but physicians that complete their residencies in rural places have a 70% probability of remaining rural. I find that primary care physicians are about 3.5 times more likely to pick a job within the same state of residency and 4 times more likely to pick a job within the same hospital referral region as the residency. On the other hand, specialists are about 2.5 times more likely to pick a job within the same state as residency and about 3 times more likely to pick a job within the same hospital referral region. I also find that top-50 residents are more difficult to be retained, while I find extremely high estimates of retention of physicians that completed their residency rurally. Due to the small sample problem, the standard errors are not reliable for yearly estimates. I therefore look at the sample as a whole and find that rural residents are at least one time more likely to be retained. Since that is estimated using the whole sample across years, I consider this to be a lower bound on the retention preference for rural residents.

I find that elasticities are, in fact, quite low, especially compared to those displayed by similarly high-skilled workers.

Finally, I use the model to analyze the performance of current policies targeted at bringing physicians to rural areas. I find that 0.5% more primary care residents and 1.3% more specialists have picked rural areas due to loan forgiveness alone. Monetary incentives in the form of bonus payments averaging $7,500 are responsible for a further 0.2% increase in primary care physicians and 0.1% increase in specialists. By retargeting the spending currently used for loan forgiveness to higher salary incentives for rural employment, I find that almost 6 times more primary care physicians would pick rural areas. Since primary care physicians are the main physician category that currently provides medical care to rural areas, and since they do not need a particular infrastructure to do so, these results suggest that policymakers should retarget spending from loan forgiveness to salary incentives and that offering salary incentives to primary care physicians only would be even more effective. The average quality of the physicians attracted under these higher salary incentives is also better compared to loan forgiveness. Another possible policy intervention suggested by the results on the high preference for retention is the use of these monetary incentives to create rural residencies. Since the residency choice is not directly modeled in this chapter, this question is outside the scope of this chapter but will be addressed in future work.

Chapter 4

Physician Workforce Effect on Health

4.1 Introduction

The effect of the physician workforce on health outcomes of the American population is a key, yet still poorly understood relationship. Considering the proposals put forward by policymakers, the American Medical Association, as well as the media, most interventions at the policy level aimed at equalizing the health outcomes and health care effectiveness across all areas in the Unites States rely on a higher presence of physicians, and in particular of primary care physicians, in the areas that currently need them the most (see, i.a., Sandy et al. 2009, Council on Graduate Medical Education 2010, Association of American Medical Colleges 2019). Nevertheless, it is problematic to show a causal relationship between the physician workforce and the health outcomes of the affected population. This chapter seeks to partially fill this gap by providing a first step toward an identification strategy for the effect of physicians on health, utilizing an instrumental variable strategy with exogenous policy shocks as well as detailed micro-data on procedure revenue.

Due to the problematic nature of determining a causal relationship between physician concentration and health outcomes, there is a substantial amount of studies of the cross-sectional data evidence in the United States (see Macinko, Starfield, and Shi 2007 for a comprehensive review of these studies; see Chang et al. 2011 for a data-based discussion on the association between physician workforce and health). Such studies have been the basis for a call for an increased physician ratio by policymakers and have been treated as empirical proof that physicians lead to better health outcomes. Nevertheless, previous papers have been based on cross-sectional analysis of the differences in mortality and physician ratio across counties or states, with some controls such as income. The issue with an approach that simply compares such geographical differences is that the unobserved and uncontrolled factors that affect both the physician ratio and the mortality lead to biased estimates of the physician workforce coefficient and tend to bias it upward. This chapter implements an instrumental-variable approach based on the procedures carried out in different areas which estimates a physician workforce effect on health equal to about 1/10 of the estimates usually generated through standard linear regression.

To better understand the bias of the coefficient of the physician workforce, it is important to realize two important data facts. First, mortality is higher in rural than in urban areas, across and within all age groups and across and within all causes of deaths. To illustrate this, the all-cause crude mortality rate in 2017 for large central metros was 722.8 compared to the noncore (most rural) area mortality rate of 1,224.8 per 100,000 residents (CDC Wonder). This holds within each age group and within each main cause of death. For example, 2011-2013 all-age heart-disease mortality rate was 166.6 in urban areas and 195 in rural areas (CDC Wonder). Second, as discussed in the previous Chapters 2 and 3, physicians are concentrated in cities, and this is true within and across specialty groups. To illustrate, as of 2013, there were approximately 68 primary care physicians per 100,000 residents in rural areas, compared to an average of 84 primary care physicians per 100,000 residents in urban areas (Petterson et al. 2013). Across specialists (in particular, surgeons), the difference is even higher, with more than double as many providers in urban areas compared to rural areas, with 131 specialists per 100,000 residents in rural areas and 312 providers per 100,000 residents in urban areas (National Center for Health Workforce Analysis 2014).

These facts clearly illustrate that cities both attract more physicians and healthier people, but whether these two facts are causally related is not as obvious. There are many variables, in fact, that are correlated with both the physician concentration and health outcomes. For example, cities are on average richer and have a much higher level of amenities, as discussed in Chapter 3. Some of these amenities relate to health outcomes: some examples can be the availability of gym, health and organic food stores, health advocacy groups and advertisement to raise awareness, health groups promoting exercise such as clubs and availability of free workout groups (such as public yoga). However, the higher amenities, as discussed in Chapter 3, also lead to a higher concentration of physicians. Since all these omitted variables are positively correlated with both the physician concentration ratio and with the population health outcomes, omitting them will bias the coefficient on the physician workforce upward with any regression analysis that does not take this endogeneity into consideration.

Another important consideration regards the definitions of geography and of mortality used across studies. First, this chapter will use hospital referral regions (HRRs) as its health markets. HRRs are defined by the Dartmouth Atlas Center as the closest proxy to a medical market, meaning that patients that live within an HRR tend to receive care within the HRR the majority of the time. Second, it is important to account for the geographical differences in age, gender, and race across the population, as not doing so also leads to mistakes in the coefficient estimation. For example, the median age of adults living in rural areas is 51 years, compared with a median age of 45 for urban areas (Census Bureau 2016). With an older population, mortality is necessarily higher due to age. Since cities tend to be younger, and physicians are more often in cities, this yet-again biases the coefficient. Moreover, to understand the impact of physicians on the mortality rate, it is simply important to account for the different demographic trends. This chapter will utilize an age-race-gender adjusted mortality rate in the analysis.

This chapter implements an instrumental-variable approach that exploits the great variation in the procedures carried out across and within areas joint with the changes in the policy-set fees for such procedures for both primary care physicians and specialists to instrument for the physician concentration. The identifying assumptions for this approach are that the instrument is well-correlated with the physician distribution and exogenous with respect to the health outcomes of patients. The first assumption is highly supported by the discussion in Chapters 2 and 3, which show that physicians highly respond to the reimbursements they receive in different areas. The second assumption is verified by looking at the known tests on instrument validity. The instruments pass the Hansen-J , the Stock-Yogo , the CLR, and the AR tests, and report a high F-test in the first-stage regression. All in all, the instruments seem to perform well in the estimation. Results from the IV estimation indicate that an increase in one more physician per 10,000 saves, on average, 4.5 lives based on an average of 4,484 deaths per 100,000 residents.

The remainder of this chapter is organized as follows: Section 4.2 presents a literature review on the topic; Section 4.3 introduces the datasets used in the chapter; Section 4.4 discusses the reduced-form approach used while Section 4.5 argues the validity of the identification strategy employed; Section 4.6 discusses the results; Section 4.7 concludes.

4.2 Literature Review

This chapter primarily contributes to the vast academic literature and reports from policy analysis addressing the relationship between the physician supply and health benefits in the United States.

Numerous studies have been carried at different geographical levels. In particular, at a state level, some of the studies carried out include Shi et al. (2012), Shi et al. (1999). Shi et al. (2005a), Shi et al. (2004), Shi et al. (2003a), and Shi et al. (2003b); at the county level, these include Joines et al. (2003), Shi et al. (2005b); at the metro-area level, these include Shi et al. (2005c) and Shi et al. (2011); at the individual level, these include Shi et al. (2002) and Shi et al. (2000). Other related papers, to mention a few, are Vogel and Ackermann (1998), Laditka (2004), Parchman (1994), Parchman and Culler (1999), Ricketts et al. (2001), and Schreiber and Zielinski (1994), and Chang (2011). A beautifully executed review and summary of these studies is available in Macinko, Starfield, and Shi (2007). The key way that this chapter differentiates itself in the literature is the attempt to determine causation using estimation methods that are common in applied microeconomics and econometrics.

This chapter also contributed to the large number of reports that are carried out by the Council on Graduate Medical Education and by the Association of American Medical Colleges (for example, refer to Council on Graduate Medical Education 2010 and Association of American Medical Colleges 2019). These institutions as well as related ones often publish reports regarding the need for more physicians and projections on the demand for healthcare, with hints at the distribution of health outcomes and its correlation with the physician supply.

Methodologically, this chapter builds on the standard and vast literature on instrumental variable estimators.

4.3 Data

The geographical unit of study is a hospital referral region (HRR), as defined by the Health Resources & Services Administration. The goal of HRRs is to define areas that are self-contained markets for primary care, so that the majority of patients living in that area go to primary care physicians within that area. The urban/rural classification follows the U.S. Census Bureau definition according to the 2013 Census criteria.

The main source of data for this chapter comes from the Centers for Medicare & Medicaid Services (CMS) and is the same data used in the other Chapters. A brief description is repeated here for convenience. The Physician and Other Supplier Public data provides information on services and procedures provided to Medicare beneficiaries by physicians. It contains information on utilization, actual Medicare reimbursement, and submitted charges. Each line of the dataset is indexed by a National Provider Identifier (NPI), which identifies each doctor in the dataset, by a Healthcare Common Procedure Coding System (HCPCS) code, which identifies every procedure carried out by each doctor, and by the place of service, indicating whether the procedures were carried out in a facility setting or not. The data is based on information from CMS administrative claims data for Medicare beneficiaries enrolled in the fee-for-service program. The data are available for calendar years 2012 through 2016 and contain the universe of physicians taking part in Medicare Part B for the fee-for-service population. There are a little over 40 million observations in the dataset across over a million of physicians in the panel. This dataset is used for the instrumental variable approach in this chapter and is particularly key for the construction of the instrument.

Data on mortality rates come from the Dartmouth Atlas Center.

4.4 Instrumental-Variables Approach

Consider a health production function given by:

$$D_{jt} = \alpha L_{jt}^{\beta_l} K_{jt}^{\beta_k} e^{\varepsilon_{jt}} \tag{48}$$

where D_j is the health output generated by j in a given year t, in this case deaths per 100,000, L_{jt} is the labor as number of physicians per 10,000, K_{jt} is the capital (the quasifixed input), which is an index of hospitals in this case, and ε_{jt} is an error term.

Taking the natural logarithm,

$$\log\left(D_{jt}\right) = \alpha + \beta_l \log\left(L_{jt}\right) + \beta_k \log\left(K_{jt}\right) + \varepsilon_{jt} \tag{49}$$

which we can rewrite as

$$d_{jt} = \alpha + \beta_l l_{jt} + \beta_k k_{jt} + \varepsilon_{jt} \tag{50}$$

where lowercase letters denote the logarithm.

Then, we utilize the standard textbook approach of an instrumental-variable GMM estimation. Then β_l, which is the parameter of interest, is estimated through the use of an instrument Z_{jt}. The instrument and its validity is further discussed in Section 4.5.

4.5 Estimation Strategy

I utilize my micro data on physicians' transactions at the procedure level for Medicare to be able to identify shocks that would affect the physician distribution while being exogenous toward the health outcomes. The identifying assumption here is that the policy-part of the reimbursement only shocks the distribution of physicians as areas that become more remunerative are more attractive, but none of this variation is related to health outcomes. In other words, an increase in an EKG rate and therefore the attractiveness of an area where physicians can carry out more EKGs cannot be related to an increase in heart diseases. Given the discussion in the previous Chapters, the policy-set fees are exogenous and not based on changes in the underlying health of the population, supporting this assumption.

In order for this to hold, the policy-set rates have to be exogenous, otherwise other issues of endogeneity could be present. Reimbursement rates change for the whole nation according to the decisions made by the reimbursement committee. Chapter 2 illustrates how the variation in the procedures carried out by different specialty groups in different areas is the key through which a policy-set fee affects the two specialty groups differently according to the location they are in. The instrument is then equal to:

$$Z_{jt}^{SP} = \sum_{i \in N_{j,t}^{SP}} \sum_{q \in treatments} \frac{N_{i,j,t}^{q,SP} * rvu_t^q}{N_{j,t}^{SP}} \tag{51}$$

$$Z_{jt}^{PC} = \sum_{i \in N_{j,t}^{PC}} \sum_{q \in treatments} \frac{N_{i,j,t}^{q,PC} * rvu_t^q}{N_{j,t}^{PC}} \tag{52}$$

where $N_{j,t}^{k}$ is the total number of primary care physicians and specialists, respectively, in HRR j in year t, $N_{i,j,t}^{q,k}$ is the number of services carried out by primary care physicians and specialists, respectively, of procedure q in HRR j in year t, and $rvu_{j,t}^{q}$ is the policy-set reimbursement associated with procedure q in year t. In other words, the instruments calculate an average value of policy-set reimbursement that a primary care physician or a specialist, respectively, receives in HRR j in year t.

This instrument will be valid, relevant, and exogenous under the following restrictions:

1. There needs to be enough variation in the exogenous amount of reimbursement received in different areas (i.e. $\sum_{q \in treatments}\left(N_{i,j,t}^{q,SP} * rvu_{j,t}^{q}\right)$ and $\sum_{q \in treatments}\left(N_{i,j,t}^{q,PC} * rvu_{j,t}^{q}\right)$ are different for different j).

   This is easily respected because of the discussion in Chapter 2 and 3, where it is clearly shown that reimbursement amounts vary greatly by location.

2. There needs to be enough variation in the mix of procedures carried out (i.e. $\left(N_{i,j,t}^{q,SP}\right)$

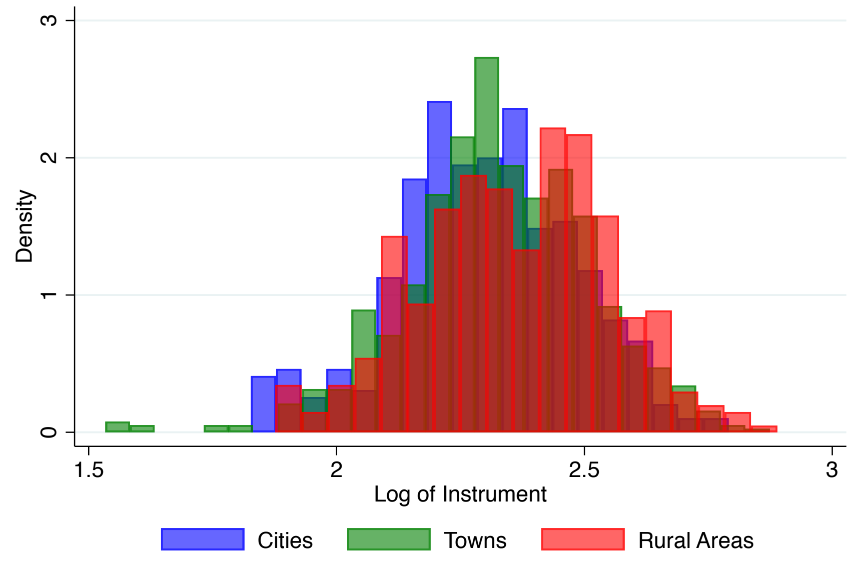


Figure 4.8: Instrument Density by Urbanity Index

Notes: This figure shows the density distribution of the instrument created, across and within urbanity types. Source: CMS.

and $\left(N_{i,j,t}^{q,PC}\right)$ are different for different q across locations and people).

This is easily respected because of the discussion in Chapter 2, where it is clearly shown that the types of procedures carried out vary a lot according to the location.

3. No procedure q is concentrated in one area only.

Therefore, I need to test the key identifying assumption that there is enough variation in the policy-set part of the reimbursement carried out in different places and that these differences in the reimbursement mix are uncorrelated with location unobservables that could affect health. First, as shown in Figure 4.8, the instrument created displays high variation across and within urbanity types.

Second, the exogeneity of the instrument could be challenged thinking that differences in

Table 4.14: Performance of the instrument: test statistics

Test	Statistic	P-value
Conditional Likelihood Ratio	218.66	0.00
Anderson and Rubin	219.52	0.00
Lagrange Multiplier	218.57	0.00
Hansen's J Test	0.95	0.33
	First-Stage Results	
Shea Partial R^2	0.6901	
Partial R^2	0.6901	
F(2, 1206)	1342.48	
P-value	0.00	

Notes: The table reports all the main statistics for tests to verify the validity of the instrument. The instrument built performs well according to all tests considered.

the policy-set reimbursement received by physicians are correlated with the same characteristics that affect the population's health outcomes. First, as mentioned above, the fees are set without relying on disease incidence and occurrence.

Instrument validity is supported by all tests. The first stage F-statistic is high and well above Stock and Yogo values, suggesting that the instrument performs well in the prediction of the physician distribution. The estimation passes the overidentification Hansen's J-test as well, with a p-value equal to 0.3295. The rule of thumb is that a high p-value indicates a good model fit, and a p-value that is not too high suggests that there are no other issues related to the model.

Table 4.14 summarizes all the test statistics.

4.6 Results

The first results analyze the effect of a higher population of physicians on the mortality of the population. All estimation is run with variables transformed in log values. Mortality rates are per 100,000 residents, while physicians are per 10,000 residents, as commonly done in the literature. The only proxy for capital is currently an index that measures the presence of hospitals within the area. The results are first reported for the commonly-run fixed-effects regression. If there is still bias in the coefficient on physician employment due to endogeneity, we would expect the parameter to be biased upward (as discussed beforehand) and therefore to be less negative. Once we run the instrumental regression analysis, the parameter becomes more negative, as theory would suggest.

The results are also broken down to show the effect in an overall physician increase per 10,000 residents independently of the specialty group, and then reports the same parameters for an increase in primary care physicians or specialists only. The parameters are very similar, suggesting that an increase in either specialty group is not inherently different from an increase in the other. This mirrors well the fact that physicians do different things in different places, as discussed in Chapters 2 and 3, so that the health care supply to the population is actually quite homogeneous across areas.

Table 4.15 reports the results of interest. Once we move from a fixed-effects to an instrumental-variable regression analysis, the parameter of interest on the employment of physicians becomes more negative, as theory would suggest. We will focus on the IV results for the remainder of this discussion. The parameter of interest is the parameter on the physician rate per 10,000 residents. The results reported suggest that a 1% increase in the number of physicians per 10,000 residents leads to a 0.19% reduction in the mortality rate per 100,000. To put this into perspective, a 1% increase in the physician rate per 10,000 residents is equivalent to an average increase of slightly less than two physicians (1.94 extra physicians per 10,000 residents on average). A decrease of 0.19% in the mortality rate per 100,000 is equivalent to, on average, 9 fewer deaths per 100,000. Therefore, on average, the effect estimated by the IV regression is that one more physician per 10,000 residents saves about 4.5 people every 100,000 residents.

The range of a 1% physician increase per 10,000 residents is equivalent to a range between <1 to 7.5 more physicians. The 0.19% decrease in the mortality rate per 100,000 residents is equivalent to a range between 6 and 11 people saved per 100,000.

The other coefficients are reasonable. The sickness of patients controls for the general sickness of the population, which increases the mortality rate, the higher it is. The hospital index is positive, which mirrors the fact that sick patients concentrate close to hospitals. The IV regression attenuates that effect, though, decreasing the coefficient to almost zero. Further research can focus on the estimation of the capital coefficient.

4.7 Conclusion

The impact of the physician workforce on health is a topic that has been analyzed for decades, with studies that have asserted a clear correlation between a higher number of physicians per capita and better health outcomes, which have been cited by policymakers and the media as empirical evidence of a causal relationship between a larger physician workforce and a healthier population. This chapter approached this issue by building a novel instrument using policy-set fees and the high variation in the procedures carried out to estimate that a physician saves, on average, 4.5 lives per 100,000 residents. This chapter

Table 4.15: Aggregate data: Fixed-effects and instrumental-variable analyses

	Fixed Effects	Instrumental Variables
All Physicians		
Physicians per 10,000	-0.08	-0.19
	(0.02)	(0.01)
Sickness of patients	0.09	0.29
	(0.03)	(0.03)
Hospital index	0.50	0.005
	(0.04)	(0.002)
Primary Care Physicians		
Physicians per 10,000	-0.05	-0.19
	(0.02)	(0.02)
Sickness of patients for primary care	-0.03	0.24
	(0.03)	(0.03)
Hospital index	0.46	0.005
	(0.05)	(0.002)
Specialists		
Physicians per 10,000	-0.08	-0.19
	(0.02)	(0.01)
Sickness of patients for specialty care	0.10	0.29
	(0.03)	(0.03)
Hospital index	0.50	0.004
	(0.04)	(0.002)

Notes: The table reports the results from the instrumental-variable approach compared to the fixed-effects regression analysis. The dependent variable is the natural logarithm of the mortality rate per 100,000 residents. All regressors are the natural logarithm of the variables. Standard errors in parentheses.

used hospital referral regions (HRRs) as the definition of health markets. HRRs are defined by the Dartmouth Atlas Center as the closest proxy to a medical market, meaning that patients that live within an HRR tend to receive care within the HRR the majority of the time. This chapter also accounted for the geographical differences in age, gender, and race across the population, as not doing so would also lead to bias in the coefficients. To understand the impact of physicians on the mortality rate, this chapter therefore utilized an age-race-gender adjusted mortality rate in the analysis.

The results shown in this chapter suggest that those reported in previous studies through a cross-sectional analysis with a few area-level controls display a large upward bias, which is typical of linear regression analyses where endogeneity is present. The results of this chapter are about 1/10 of the physician workforce effect on health estimated by previous studies. All tests on the instrument provide evidence that the instrument performs well and is exogenous to the mortality rate of the area. One more issue remain to be addressed, however: are the 4.5 lives saved because of access to a greater workforce or because of a better workforce overall? Future research needs to address this important, yet often overlooked, point.

References

1. Acemoglu, Daron, Amy Finkelstein, and Matthew J. Notowidigdo. “Income and Health Spending: Evidence from Oil Price Shocks.” *Review of Economics and Statistics* 95.4 (2013): 1079-1095.

2. Agarwal, Nikhil. “An Empirical Model of the Medical Match.” *American Economic Review* 105.7 (2015): 1939-78.

3. American Hospital Association. “Physician Ownership and Self-Referral in Hospitals: Research on Negative Effects Grows.” *Trendwatch*. (April 2008).

4. Anderson, Gerard F., et al. “Health Spending in the United States and the Rest of the Industrialized World.” *Health Affairs* 24.4 (2005): 903-914.

5. Armour, Brian S., et al. “The Effect of Explicit Financial Incentives on Physician Behavior.” *Archives of Internal Medicine* 161.10 (2001): 1261-1266.

6. Association of American Medical Colleges. *The Complexities of Physician Supply and Demand: Projections from 2017 to 2032*. Washington, D.C., April 2019.

7. Autor, David H., and David Dorn. “The Growth of Low-Skill Service Jobs and the Polarization of the US Labor Market.” *American Economic Review* 103.5: 1553-97.

8. Baker, Laurence C. “The Effect of HMOs on Fee-For-Service Health Care Expenditures: Evidence from Medicare.” *Journal of Health Economics* 16.4 (1997): 453-481.

9. Barro, Jason, and Nancy Beaulieu. “Selection and Improvement: Physician Responses to Financial Incentives.” National Bureau of Economic Research Working Paper 10017 (2003).

10. Berry, Christopher R., and Edward L. Glaeser. “The Divergence of Human Capital Levels Across Cities.” *Papers in Regional Science* 84.3: 407-44.

11. Berry, Steven, James Levinsohn, and Ariel Pakes. “Automobile Prices in Market Equilibrium.” *Econometrica: Journal of the Econometric Society* (1995): 841-890.

12. Blomqvist, Ake, and Colin Busby. “How to Pay Family Doctors: Why ’Pay Per Patient’ Is Better than Fee for Service.” *C.D. Howe Institute Commentary* 365 (2012).

13. Broomberg, J., and M. R. Price. “The Impact of the Fee-For-Service Reimbursement System on the Utilisation of Health Services. Part I. A Review of the Determinants of Doctors’ Practice Patterns.” *South African Medical Journal* 78.3 (1990): 130-132.

14. Card, David. “Immigration and Inequality.” *American Economic Review* 99.2: 1-21.

15. Card, David, and Thomas Lemieux. “Can Falling Supply Explain the Rising Return to College for Younger Men? A Cohort-Based Analysis.” *Quarterly Journal of Economics* 116.2: 705-46.

16. Chaix-Couturier, Carine, et al. “Effects of Financial Incentives on Medical Practice: Results from a Systematic Review of the Literature and Methodological Issues.” *International Journal for Quality in Health Care* 12.2 (2000): 133-142.

17. Clemens, Jeffrey, and Joshua D. Gottlieb: “Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?.” *The American Economic Review* 104.4 (2014): 1320-1349.

18. —. “In the Shadow of a Giant: Medicare's Influence on Private Physician Payments.” *Journal of Political Economy* 125.1 (2017): 1-39.

19. Colas, Mark. “Dynamic Responses to Immigration.” Opportunity & Inclusive Growth Institute Working Paper 6 (2018).

20. Cooper, James K., et al. “Rural or Urban Practice: Factors Influencing the Location Decision of Primary Care Physicians.” *Inquiry* 12.1 (1975): 18-25.

21. Cooper, Richard A., et al. “Economic and Demographic Trends Signal an Impending Physician Shortage.” *Health Affairs* 21.1 (2002): 140-154.

22. Council on Graduate Medical Education. *Twentieth Report: Advancing Primary Care*. Rockville, MD, 2010.

23. Croxson, Bronwyn, Carol Propper, and Andy Perkins. “Do Doctors Respond to Financial Incentives? UK Family Doctors and the GP Fundholder Scheme.” *Journal of Public Economics* 79.2 (2001): 375-398.

24. Diamond, Rebecca. “The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000.” *American Economic Review* 106.3 (2016): 479-524.

25. Dunne, Timothy, et al. “Entry, Exit, and the Determinants of Market Structure.” *RAND Journal of Economics* 44.3 (2013): 462-487.

26. Emanuel, Ezekiel J., and Victor R. Fuchs. “The Perfect Storm of Overutilization.” *Journal of the American Medical Association* 299.23 (2008): 2789-2791.

27. Finkelstein, Amy. “The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare.” *Quarterly Journal of Economics* 122.1 (2007): 1-37.

28. Fisher, Elliott S., et al. "The Implications of Regional Variations in Medicare Spending. Part 1: The Content, Quality, and Accessibility of Care." *Annals of Internal Medicine* 138.4 (2003): 273-287.

29. Gawande, Atul, and BBC Audiobooks America. *Better: A Surgeon's Notes on Performance*. Picador, 2008.

30. Ginsburg, Paul B. "Fee-For-Service Will Remain a Feature of Major Payment Reforms, Requiring More Changes in Medicare Physician Payment." *Health Affairs* 31.9 (2012): 1977-1983.

31. Gosden, Toby, et al. *Capitation, Salary, Fee-For-Service and Mixed Systems of Payment: Effects on the Behaviour of Primary Care Physicians*. The Cochrane Library, 2000.

32. Grant, Darren. "Physician Financial Incentives and Cesarean Delivery: New Conclusions from the Healthcare Cost and Utilization Project." *Journal of Health Economics* 28.1 (2009): 244-250.

33. Gruber, Jonathan, and Maria Owings. "Physician Financial Incentives and Cesarean Section Delivery." National Bureau of Economic Research Working Paper 4933 (1994).

34. Grumbach, Kevin, et al. "Primary Care Physicians' Experience of Financial Incentives in Managed-Care Systems." *New England Journal of Medicine* 339.21 (1998): 1516-1521.

35. Hall, Robert E., and Charles I. Jones. "The Value of Life and the Rise in Health Spending." *Quarterly Journal of Economics* 122.1 (2007): 39-72.

36. Hellinger, Fred J. "The Impact of Financial Incentives on Physician Behavior in Managed Care Plans: A Review of the Evidence." *Medical Care Research and Review* 53.3 (1996): 294-314.

37. Hemenway, David, et al. "Physicians' Responses to Financial Incentives: Evidence from a For-Profit Ambulatory Care Center." *New England Journal of Medicine* 322.15 (1990): 1059-1063.

38. Hendee, William R., et al. "Addressing Overutilization in Medical Imaging." *Radiology* 257.1 (2010): 240-245.

39. Hickson, Gerald B., William A. Altemeier, and James M. Perrin. "Physician Reimbursement by Salary or Fee-For-Service: Effect on Physician Practice Behavior in a Randomized Prospective Study." *Pediatrics* 80.3 (1987): 344-350.

40. Hillman, Alan L. “Financial Incentives for Physicians in HMOs.” *New England Journal of Medicine* 317.27 (1987): 1743-1748.

41. Hillman, Alan L., Mark V. Pauly, and Joseph J. Kerstein. “How Do Financial Incentives Affect Physicians’ Clinical Decisions and the Financial Performance of Health Maintenance Organizations?.” *New England Journal of Medicine* 321.2 (1989): 86-92.

42. Jacobson, Mireille, et al. “Does Reimbursement Influence Chemotherapy Treatment for Cancer Patients?.” *Health Affairs* 25.2 (2006): 437-443.

43. Joines, Jerry D., et al. “A Spatial Analysis of County-Level Variation in Hospitalization Rates for Low Back Problems in North Carolina.” *Social Science & Medicine* 56.12 (2003): 2541-2553.

44. Katz, Lawrence F., and Kevin M. Murphy. 1992. “Changes in Relative Wages, 1963-1987: Supply and Demand Factors.” *Quarterly Journal of Economics* 107.1 (1992): 35-78.

45. Kirch, Darrell G., Mackenzie K. Henderson, and Michael J. Dill. “Physician Workforce Projections in an Era of Health Care Reform.” *Annual Review of Medicine* 63 (2012): 435-445.

46. Kulka, Amrita, and Dennis McWeeny. “Rural Physician Shortages and Policy Intervention.” Working Paper (2018).

47. Laditka, James N. “Physician Supply, Physician Diversity, and Outcomes of Primary Health Care for Older Persons in the United States.” *Health & Place* 10.3 (2004): 231-244.

48. Lee, Sanghoon. “Ability Sorting and Consumer City.” *Journal of Urban Economics* 68.1 (2010): 20-33.

49. Leonardson, Gary, Rene Lapierre, and Doneen Hollingsworth. “Factors Predictive of Physician Location.” *Journal of Medical Education* 60.1 (1985): 37-43.

50. Levin, David C., and Vijay M. Rao. “Turf Wars in Radiology: The Overutilization of Imaging Resulting from Self-Referral.” *Journal of the American College of Radiology* 5.7 (2008): 806-810.

51. McElduff, P., et al. “Will Changes in Primary Care Improve Health Outcomes? Modelling the Impact of Financial Incentives Introduced to Improve Quality of Care in the UK.” *Quality and Safety in Health Care* 13.3 (2004): 191-197.

52. Melichar, Lori. “The Effect of Reimbursement on Medical Decision Making: Do Physicians Alter Treatment in Response to a Managed Care Incentive?.” *Journal of Health Economics* 28.4 (2009): 902-907.

53. Moretti, Enrico. "Real Wage Inequality." *American Economic Journal: Applied Economics* 5.1 (2013): 65-103.

54. National Center for Health Workforce Analysis. *Distribution of U.S. Health Care Providers Residing in Rural and Urban Areas*. 2014.

55. Nevo, Aviv. "Empirical Models of Consumer Behavior." *Annual Review of Economics* 3.1 (2011): 51-75.

56. —. "Measuring market power in the ready-to-eat cereal industry." *Econometrica* 69.2 (2001): 307-342.

57. —. "A Practitioner's Guide to Estimation of Random-Coefficients Logit Models of Demand." *Journal of Economics & Management Strategy* 9.4 (2000): 513-548.

58. Petterson, Stephen. "Unequal Distribution of the U.S. Primary Care Workforce." *Graham Center Policy One-Pager* (Jun. 1, 2013).

59. Parchman, Michael L., and Steven Culler. "Primary Care Physicians and Avoidable Hospitalizations." *Journal of Family Practice* 39.2 (1994): 123-129.

60. Parchman, Michael L., and Steven D. Culler. "Preventable Hospitalizations in Primary Care Shortage Areas: An Analysis of Vulnerable Medicare Beneficiaries." *Archives of Family Medicine* 8.6 (1999): 487.

61. Pham, Hoangmai H., and Paul B. Ginsburg. "Unhealthy Trends: The Future of Physician Services." *Health Affairs* 26.6 (2007): 1586-1598.

62. Rasmusen, Eric. *The BLP Method of Demand Curve Estimation in Industrial Organization*. Department of Business Economics and Public Policy, Kelley School of Business, Indiana University, 2007.

63. Ricketts, Thomas C., et al. "Hospitalization Rates as Indicators of Access to Primary Care." *Health & Place* 7.1 (2001): 27-38.

64. Rosenblatt, Roger A., and L. Gary Hart. "Physicians and Rural America." *Western Journal of Medicine* 173.5 (2000): 348.

65. Safran, Dana Gelb, Alvin R. Tarlov, and William H. Rogers. "Primary Care Performance in Fee-For-Service and Prepaid Health Care Systems: Results from the Medical Outcomes Study." *Journal of the American Medical Association* 271.20 (1994): 1579-1586.

66. Sandy, Lewis G., et al. "The Political Economy of US Primary Care." *Health Affairs* 28.4 (2009): 1136-1145.

67. Schreiber, Steven, and Teresa Zielinski. “The Meaning of Ambulatory Care Sensitive Admissions: Urban and Rural Perspectives.” *Journal of Rural Health* 13.4 (1997): 276-276

68. Scott, Anthony, et al. “The Effect of Financial Incentives on the Quality of Health Care Provided by Primary Care Physicians.” *Cochrane Database of Systematic Reviews* 2011.9 (2010).

69. Shi, Leiyu, et al. “Primary Care, Race, and Mortality in US states.” *Social Science & Medicine* 61.1 (2005a): 65-75.

70. Shi, Leiyu, et al. “Primary Care, Social Inequalities, and All-Cause, Heart Disease, and Cancer Mortality in US Counties, 1990.” *American Journal of Public Health* 95.4 (2005b): 674-680.

71. Shi, Leiyu, et al. “Primary Care, Social Inequalities, and All-Cause, Heart Disease, and Cancer Mortality in US Counties: A Comparison of Urban and Rural Areas.” *Public Health* 119.8 (2005c): 699-710.

72. Shi, Leiyu, et al. “Primary Care, Infant Mortality, and Low Birth Weight in the States of the USA.” *Journal of Epidemiology & Community Health* 58.5 (2004): 374-380.

73. Shi, Leiyu, et al. “The Relationship between Primary Care, Income Inequality, and Mortality in US States, 1980–1995.” *J. Am. Board Fam. Pract.* 16.5 (2003a): 412-422.

74. Shi, Leiyu, et al. “Primary Care, Income Inequality, and Stroke Mortality in the United States: A Longitudinal Analysis, 1985–1995.” *Stroke* 34.8 (2003b): 1958-1964.

75. Shi, Leiyu, et al. “Primary Care, Self-Rated Health, and Reductions in Social Disparities in Health.” *Health Services Research* 37.3 (2002): 529-550.

76. Shi, Leiyu, and Barbara Starfield. “The Effect of Primary Care Physician Supply and Income Inequality on Mortality among Blacks and Whites in US Metropolitan Areas.” *American Journal of Public Health* 91.8 (2001): 1246-1250.

77. Shi, Leiyu, and Barbara Starfield. “Primary Care, Income Inequality, and Self-Rated Health in the United States: a Mixed-Level Analysis.” *International Journal of Health Services* 30.3 (2000): 541-555.

78. Shi, Leiyu, et al. “Income Inequality, Primary Care, and Health Indicators.” *J. Fam. Pract.* 48 (1999): 275–284.

79. Shrank, William, et al. “Effect of Physician Reimbursement Methodology on the Rate and Cost of Cataract Surgery.” *Archives of Ophthalmology* 123.12 (2005): 1733-1738.

80. Stearns, Sally C., Barbara L. Wolfe, and David A. Kindig. "Physician Responses to Fee-For-Service and Capitation Payment." *Inquiry* (1992): 416-425.

81. Steele, Henry B., and Gaston V. Rimlinger. "Income Opportunities and Physician Location Trends in the United States." *Economic Inquiry* 3.2 (1965): 182-194.

82. United States Census Bureau. *New Census Data Show Differences Between Urban and Rural Populations*. Dec. 8, 2016.

83. —. Census 2010 PMSA Definition:

    https://www.census.gov/population/estimates/metro-city/99mfips.txt

84. Vincent, David W. "The Berry–Levinsohn–Pakes Estimator of the Random-Coefficients Logit Demand Model." *Stata Journal* 15.3 (2015): 854-880.

85. Vogel, Robert L., and Richard J. Ackermann. "Is Primary Care Physician Supply Correlated with Health Outcomes?." *International Journal of Health Services* 28.1 (1998): 183-196.

Appendix A: Appendix to Chapter 2

A.8 Institutional Framework

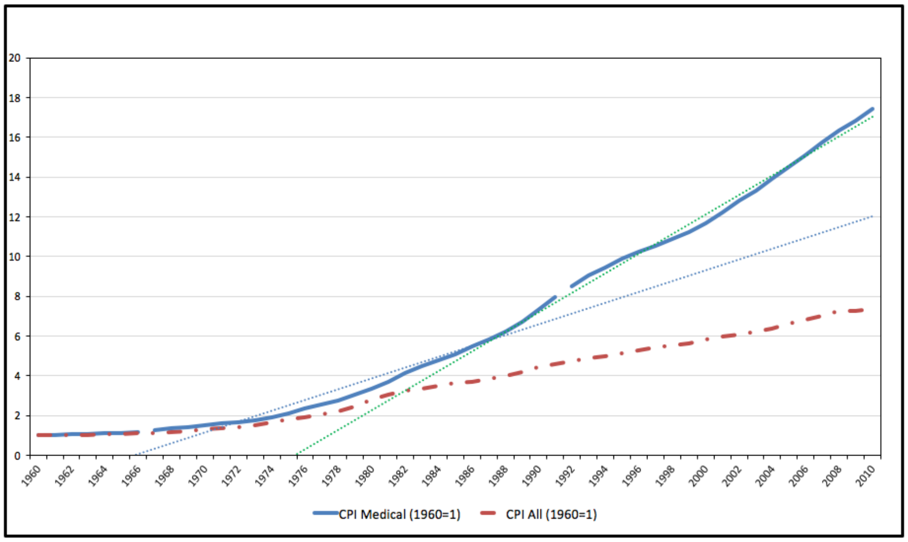


Figure A.1: Medical CPI vs. All CPI

Notes: This figure shows the Consumer Pricing Index for all goods vs. only medical goods. The growth of CPI for medical goods changed dramatically both following the birth of Medicare in 1967 and the birth of the Resource-Based Relative Value Unit System in 1992. Source: CMS.

As shown in Figure A.1, the increase in health expenditure has been long-lasting, with a clear increase in its growth since the 80s. The first full year under Medicare coverage (1967) clearly led to an increase in medical costs.

The 1992 fee-for-service system is called the Resource-Based Relative Value Scale (RBRVS). The system was based on some initial rates and geographical adjustment factors, which would be reviewed on an annual basis by the RVS Update Committee (RUC). The RUC was meant to only have an advisory role, but its recommendations are accepted 97% of the time, making it *de facto* the fee-setting organization.

The Reader should bear in mind that the fee-for-service system is not new to 1992. The system before, the Usual, Customary, and Reasonable (UCR) system, was still based on a fee-for-service reimbursement; however, these reimbursements were not standardized across doctors and tractability was not possible also due to lack of information on individual pricing. This is what prompted discussions at the beginning of 1990 to reform it. This paper shows that the new pricing system exacerbated the issue, leading to a change in doctors' decision making. Moreover, it allows the researcher to be able to estimate the impact of this pricing on physicians' choices due to the fee standardization (and its availability publicly).

For each procedure j in market t, the reimbursement is equal to:

$$Reimbursement_{jt} = Constant_t * RVU_{jt} * GAF_t \tag{53}$$

The constant only depends on the year and is equal across specialties and procedures. The relative value units change according to the procedure as well as the year, and the geographic adjustment factors (GAFs) depend on the market (area and year).

The constant, called the Conversion Factor (CF), is a national adjustment factor, which is identical across specialties, areas, and procedures. The 2017 CF is equal to \$35.8887. The GAFs are a proxy for cost of living, adjusting for differences in input costs across payment regions.

The RUC's recommendations across the years have been constantly widening the gap between the procedure reimbursements usually carried out by specialists and those regularly carried out by primary care.

Since the reimbursement does not depend on who carries out the procedure, but only on the procedure itself, and specialty procedures are more highly priced than typical primary care procedures, this payment system generates financial incentives for primary care physicians to substitute to more specialized, remunerative procedures when possible.

A.9 Standard Multinomial Logit Demand

This section presents what the model would look like if it was simplified to a standard multinomial logit model of demand.

I assume the household to face the following utility function when buying product j in market t:

$$\begin{aligned} u_{ijt} &= x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt} + \varepsilon_{ijt} \qquad \varepsilon_{ijt} \text{ iid} \sim \text{T1EV} \\ \delta_{jt} &= x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt} \end{aligned}$$

Markets, products, and characteristics are the same as in Section 5.

The simple logit demand assumes all individuals to be identical. Then, the market share of product j is equal to the probability that product j yields the highest utility, which happens if the ε disturbance of product j is high enough with respect to the alternatives:

$$s_{jt} = \Pr\left(x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt} + \varepsilon_{ijt}\right) > \Pr\left(x_{kt}\beta + \lambda RVU_{kt} - \alpha p_{kt} + \varepsilon_{ikt}\right) \quad \forall k \neq j \tag{54}$$

Thanks to the properties of the type-1 extreme value distribution, this reduces to the share of product j being equal to:

$$s_{jt} = \frac{\exp\left\{x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt}\right\}}{1 + \sum_{k=1}^{1175} \exp\left\{x_{kt}\beta + \lambda RVU_{kt} - \alpha p_{kt}\right\}} \tag{55}$$

To estimate this demand, notice that:

$$\begin{aligned}
\log\left(\frac{s_{jt}}{s_{0t}}\right) &= \\
\log(s_{jt}) - \log(s_{0t}) &= \log\left(\frac{\exp\left\{x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt}\right\}}{1 + \sum_{k=1}^{1175} \exp\left\{x_{kt}\beta + \lambda RVU_{kt} - \alpha p_{kt}\right\}}\right) \\
&\quad - \log\left(\frac{\exp\{0\}}{1 + \sum_{k=1}^{1175} \exp\left\{x_{kt}\beta + \lambda RVU_{kt} - \alpha p_{kt}\right\}}\right) \\
\log(s_{jt}) - \log(s_{0t}) &= \log\left(\exp\left\{x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt}\right\}\right) \\
&\quad - \log\left(1 + \sum_{k=1}^{1175} \exp\left\{x_{kt}\beta + \lambda RVU_{kt} - \alpha p_{kt}\right\}\right) \\
&\quad - \log(\exp\{0\}) + \log\left(1 + \sum_{k=1}^{1175} \exp\left\{x_{kt}\beta + \lambda RVU_{kt} - \alpha p_{kt}\right\}\right) \\
\log(s_{jt}) - \log(s_{0t}) &= \log\left(\exp\left\{x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt}\right\}\right) - \log(1) \\
\log(s_{jt}) - \log(s_{0t}) &= x_{jt}\beta + \lambda RVU_{jt} - \alpha p_{jt}
\end{aligned}$$

As I mentioned before, even though I expect the price to be exogenous, I still use an instrumental variable approach. The instruments are the same as the ones presented in the body of the text.

A.10 Model-Implied Marginal Cost Regression on Input Costs

Table A.1 shows the results from a regression of the instruments discussed in Section 2.6 on price. The instruments explain about 54% of the price variance with highly significant

Table A.1: OLS Regression of Price on Chosen Instruments

Variables	y = Price
Procedure GAF	840.80
	(52.15)
Practice Expense GAF	-82.06
	(23.40)
Malpractice GAF	13.18
	(5.59)
Malpractice Reimbursement	748.50
	(1.83)
Constant	-677.70
	(49.00)
Observations	142,112
R^2	0.54

Notes: This table shows the coefficients obtained by regressing price on the chosen instrumental variables. Standard errors in parentheses.

coefficients.

The marginal costs can be backed out from the estimates of the model. Table A.2 shows the results from a regression of the marginal costs implied by the model on the instrumental variables chosen for a random market, i.e., rural Kansas. Marginal costs are well fitted by the instrumental variables representing input costs, with an R^2 equal to 0.74.

A.11 Robustness of Reimbursement Effect on Probability

Table A.3 shows the results from the logistic regression as explained in Section 2.6 on a widened range of procedures, carried out by specialists 50 to 80% of the time, and by primary care physicians the remainder of the time. The positive effect of the reimbursement rate is consistent. The increase in the probability of providing specialty procedures, independently of the number of services provided, is about the same as before. Once I include frequency weights, the probability is about half. This is due to the fact that I am now including many procedures that are generally provided by primary care physicians to begin

Table A.2: Regression of Marginal Costs on Cost Shifters, Rural Kansas

Variables	(1)	(2)
Work GAF	774.20	766.19
	(1.68)	(1.66)
Practice GAF	-72.10	-71.67
	(1.74)	(1.73)
Malpractice Insurance GAF	0.07	0.07
	(1.40)	(1.39)
Work GAF^2	-417.51	-413.38
	(1.69)	(1.66)
Malpractice Insurance	0.42	0.42
	(13.71)	(13.67)
Malpractice Insurance^2	-0.04	-0.04
	(6.81)	(6.80)
Work GAF*Practice GAF	71.53	71.12
	(1.74)	(1.73)
Random Error		-0.004
		(0.44)
Constant	-353.80	-349.93
	(1.65)	(1.63)
R^2	0.74	0.75
Observations	272	272

Notes: Exemplary results for one market. Marginal costs estimated are regressed on the instrumental variables used in the paper, showing a good fit of cost variance. T-Statistics in parentheses.

with, so that these procedures are more homogeneously carried out across the physician population.

Table A.3: Logit: y=1 if primary care physicians increase the number of specialty procedures carried out - 20-50%

Variables	(1)	(2)
Change in Procedure Reimbursement	0.14	0.21
	(0.02)	(0.003)
Change in Malpractice Reimbursement	-0.62	-2.00
	(0.03)	(0.01)
Change in Practice Reimbursement	0.02	0.50
	(0.01)	(0.001)
Change in Procedure GAF	10.30	32.83
	(1.40)	(0.15)
Change in Malpractice GAF	-0.003	0.17
	(0.02)	(0.002)
Change in Practice GAF	-2.64	-7.34
	(0.56)	(0.06)
Constant	1.77	2.58
	(0.003)	(0.0003)
Frequency Weights	NO	YES
Observations	2,304,888	2,304,888

Notes: Logistic regression of variables of interest on whether or not primary care increases the specialty procedures provided, with and without frequency weights. The procedures included are those that are carried out by primary care physicians, on average, between 20 and 50% of times as suggested by the specialization index previously discussed. Year dummies are included. Standard errors in parentheses.

Appendix B: Appendix to Chapter 3

B.12 Preference for Retention

Table 9 reports the results for physicians' preferences for retention. Physicians display a preference for locations that are close to where they completed their residency. Therefore, preferences of workers with the same demographic characteristics ℓ for a HRR j can differ due to preferences to remain within the residency's HRR and state. This is motivated by two facts in the health literature: first, many physicians that want to return to their state of birth tend to pick a residency that already fulfills their preference, so this preference also proxies for a preference to return to the birthplace; secondly, many medical students initiate personal relationships during residency that lead to their choice of remaining close to their residency location (often due to the fact that their spouse is not in the medical profession, for example). These two facts lead to a third, widely discussed fact: many states display high rates of residency retention, with 54% of all residents in the US remaining within their state of residency for their first job. My data sample replicates this fact, with 51.4% of doctors picking to remain within the same state of residency.

Table B.1: Physician Supply: Preferences for Retention ($\beta^{k,\ell}_{state}$, $\beta^{k,\ell}_{HRR}$)

	State		State, Top 50		HRR		HRR, Top 50	
	PC	SP	PC	SP	PC	SP	PC	SP
2012	2.17	1.84	0.65	-0.32	2.79	2.11	-1.38	-0.26
	(0.08)	(0.06)	(0.41)	(0.12)	(0.09)	(0.06)	(0.50)	(0.13)
2013	2.14	1.56	0.52	-0.53	2.83	2.02	0.13	-0.14
	(0.08)	(0.06)	(0.42)	(0.15)	(0.09)	(0.07)	(0.70)	(0.16)
2014	2.54	1.60	-1.02	-0.59	2.81	2.10	0.58	-0.23
	(0.07)	(0.06)	(0.35)	(0.14)	(0.08)	(0.07)	(0.45)	(0.15)
2015	2.63	1.75	-0.33	-0.31	2.78	2.01	-0.67	-0.60
	(0.08)	(0.06)	(0.29)	(0.14)	(0.09)	(0.07)	(0.40)	(0.16)
2016	2.59	1.79	0.72	-0.45	3.10	2.10	-0.95	-0.43
	(0.08)	(0.06)	(0.42)	(0.13)	(0.09)	(0.07)	(0.45)	(0.15)

Notes: These results come from the physician supply analysis described in the paper. Magnitude represents the semielasticity of demand with respect to whether the choice is within the same state or area (HRR) of residency, respectively. The coefficients are obtained through maximum likelihood estimation of the conditional logit model based on individual-level data on residency and choice locations. The sample includes all residents finishing residency, by specialty, between 2012 and 2016. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas.

Table 9 shows the estimates from the maximum likelihood estimation of the conditional logit model displaying the semi-elasticity of demand with respect to whether or not the choice is within the same state of residency first, and within the same hospital referral region after. The first two columns report the results for state of residency, while the second two columns report the results for state of residency. I find that primary care physicians are about 3.5 times more likely to pick a job within the same state of residency and about 4 times more likely to pick a job within the same hospital referral region as the residency. On the other hand, specialists are 2.5 times more likely to pick a job within the same state as residency and about 3 times more likely to pick a job within the same hospital referral region. Further checks reject that retention values can be the same between primary care physicians and specialists.

The retention value of staying within the same hospital referral region displays an increase of 11% in the last five years, suggesting that primary care physicians value retention more and more. The value of staying within the same state for primary care physicians has also displayed an increase over the panel period analyzed, by a little over 19%. Specialists' preference to stay within the same state as residency has remained fairly constant across the panel.

I compare the base estimates with those of individuals that attended a top-50 residency. These last estimates seem to be more noisy, due to the small selected sample. I cannot conclude that top-50 primary care residents have a different value to remain within the same state of residency, but top-50 primary care residents have a lower value to remain within the same hospital referral region. Top-50 specialty residents display a lower value of retention, and they are about 1-1.5 times less likely to be retained at the hospital referral region- and state-level, across all years.

Finally, I find extremely high estimates of retention of physicians that completed their residency rurally. Due to the small sample problem, the standard errors are not reliable for yearly estimates. I therefore look at the sample as a whole and find that rural residents are at least one time more likely to be retained. Since that is estimated using the whole sample across years, I consider this to be a lower bound on the retention preference for rural residents.

B.13 Unobserved Amenities

From the results obtained paper, I can quickly solve for the implied unobserved preferences for the different job locations. I can then look at whether the unobserved amenities for primary care physicians are related to the unobserved amenities for specialists. Table 10 presents these estimates.

Table B.2: Unobserved Amenities Implied by the Model

	ΔUnobserved Amenities, Primary Care
ΔUnobserved Amenities, Specialists	0.33
Constant	0.26
R^2	0.16

Notes: The regression uses the unobserved characteristics backed up from the model of physician supply. Changes in the specialists' utility value of unobserved characteristics are correlated with changes in the primary care physicians' value for the same location.

The specialists' utility value of changes in unobserved amenities is positively correlated with the primary care physicians' utility value of changes in unobserved amenities for the same location. The variation explained is about 16%. While this is not too high, there are many things that specialists could value more than primary care physicians, such as the presence of hospitals at close proximity, where specialists often have an office and perform procedures.

To see whether the estimations make sense, I rank the locations based on the unobserved amenities for primary care physicians and specialists.

I find that the top locations for unobservables for specialists are: Houston, New York, Miami, Philadelphia, Atlanta, Dallas. All of these are big cities with a high concentration of hospitals and are well-known as desirable locations, reinforcing the validity of the results.

B.14 Evolution of Welfare Differences between Primary Care Physicians and Specialists

The wage differential as well as the reimbursement differential between primary care physicians and specialists has been increasing over time. The differences are calculated using log hourly wages for specialists and primary care and the average is taken across all hospital referral regions for every year. The increase in the wage gap between primary care physicians and specialists in the past 5 years has been equal to 0.037 log units (over $1/hour).

I calculate the welfare as follows:

$$\text{Welfare}_t^k = \log\left(\sum_j \exp\left(\delta_{jt}^{k,\ell} + \beta_j^{k,\ell} x_{ijt} + \varepsilon_{ijt}\right)\right) \tag{56}$$

I then measure the physician's willingness to pay (in log wages) to pick his first choice counterfactual hospital referral region instead of his first choice hospital referral region in 2012. I look at the expected utility change driven by different factors and calculate the average welfare gap between specialists and primary care physicians resulting from such differences.

In particular the change in the welfare gap between specialists and primary care physicians in year t is given by the following:

$$\Delta\text{Welfare Gap}_t = \left(\text{Welfare}_t^{SP} - \text{Welfare}_t^{PC}\right) - \left(\text{Welfare}_{2012}^{SP} - \text{Welfare}_{2012}^{PC}\right) + \left(w_{2012}^{SP} - w_{2012}^{PC}\right) + \left(reimb_{2012}^{SP} - reimb_{2012}^{PC}\right) \tag{57}$$

The results from the four different welfare gap analyses (total compensation, total compensation with rents and amenities, and all factors) are reported in Table 11. I find that only considering the wage gap represents well the welfare gap caused by differences in the total compensation between specialists and primary care physicians. However, once everything else is taken into account (rent, amenities), the wage gap alone only captures a fifteenth of the welfare gap between the two physician groups.

I then calculate the same gap by analyzing the differences along the urbanity index, differentiating among big cities, small cities, and rural areas. The current wage gap is highest in big cities, at 0.097, as expected, since physicians are compensated more in places with lower amenities.

Once the geographical differences are taken into consideration, I find that considering only the compensation dramatically understates the welfare gap between the two types of physi-

Table B.3: Welfare Decomposition: All Locations

	ΔCompensation	ΔCompensation, Rent, Amenities	ΔAll
2012	1.36	1.36	1.36
2013	1.36	1.26	2.11
2014	1.24	1.09	2.31
2015	1.31	1.24	2.09
2016	1.40	1.51	1.93
Δ2016-2012	0.04	0.15	0.57
$\frac{\Delta\text{Welfare Gap}}{\Delta\text{Wage Gap}}$	1.10	4.16	15.48

Notes: These results come from the welfare analysis described in the paper. I measure the physician's willingness to pay (in log wages) to pick his first choice counterfactual location instead of his first choice location in 2012. I then analyze the expected utility change driven by different factors and calculate the average welfare gap between specialists and primary care physicians in the different environments. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas. I account for the initial wage gap, reimbursement gap, and reimbursement rate gap observed in the data. The initial wage gap between primary care physicians and specialists in the past 5 years is equal to 0.037 log units (over $1/hour). More details on the estimation are available in the text.

cians rurally. Compensation alone is not a good proxy of the welfare gap due to the higher wages that make up for lost amenities. All results from the decomposition by geographical area are reported in Tables 12 through 14.

Table B.4: Welfare Decomposition by Location Urbanity: Compensation

ΔCompensation	All	City	Small City	Rural
2012	1.36	1.16	1.41	1.43
2013	1.36	1.18	1.38	1.38
2014	1.24	1.11	1.36	1.10
2015	1.31	1.17	1.36	1.29
2016	1.40	1.19	1.47	1.40
Δ2016-2012	0.04	0.03	0.06	-0.03
$\frac{\Delta\text{Welfare Gap}}{\Delta\text{Wage Gap}}$	1.10	0.30	3.00	-1.11

Notes: These results come from the welfare analysis described in the paper. I measure the physician's willingness to pay (in log wages) to pick his first choice counterfactual location instead of his first choice location in 2012. I then analyze the expected utility change driven by changes in compensation and calculate the average welfare gap between specialists and primary care physicians along the urbanity index. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas. I account for the initial wage gap, reimbursement gap, and reimbursement rate gap observed in the data. The initial wage gap between primary care physicians and specialists in the past 5 years is equal to 0.097 log units in cities, 0.020 log units in small cities, and 0.028 log units in rural areas. More details on the estimation are available in the text.

Table B.5: Welfare Decomposition by Location Urbanity: Compensation, Rent, Amenities

ΔCompensation, Rent, Amenities	All	City	Small City	Rural
2012	1.36	1.16	1.41	1.43
2013	1.26	1.12	1.28	1.24
2014	1.09	1.07	1.43	0.84
2015	1.24	1.28	1.28	1.30
2016	1.51	1.39	1.53	1.38
Δ2016-2012	0.15	0.22	0.12	-0.05
$\frac{\Delta\text{Welfare Gap}}{\Delta\text{Wage Gap}}$	4.16	2.29	6.05	-1.78

Notes: These results come from the welfare analysis described in the paper. I measure the physician's willingness to pay (in log wages) to pick his first choice counterfactual location instead of his first choice location in 2012. I then analyze the expected utility change driven by changes in compensation, rent, and amenities and calculate the average welfare gap between specialists and primary care physicians along the urbanity index. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas. I account for the initial wage gap, reimbursement gap, and reimbursement rate gap observed in the data. The initial wage gap between primary care physicians and specialists in the past 5 years is equal to 0.097 log units in cities, 0.020 log units in small cities, and 0.028 log units in rural areas. More details on the estimation are available in the text.

Table B.6: Welfare Decomposition by Location Urbanity: All Factors

ΔCompensation, Rent, Amenities	All	City	Small City	Rural
2012	1.36	1.16	1.41	1.43
2013	2.11	1.91	2.16	2.19
2014	2.31	2.12	2.37	2.37
2015	2.09	1.89	2.15	2.18
2016	1.93	1.73	1.98	2.03
Δ2016-2012	0.57	0.57	0.57	0.60
$\frac{\Delta\text{Welfare Gap}}{\Delta\text{Wage Gap}}$	15.48	5.87	28.58	21.50

Notes: These results come from the welfare analysis described in the paper. I measure the physician's willingness to pay (in log wages) to pick his first choice counterfactual location instead of his first choice location in 2012. I then analyze the expected utility change driven by the intertemporal changes in the different factors and calculate the average welfare gap between specialists and primary care physicians along the urbanity index. The choice set is given by the set of hospital referral regions in the United States as defined by Dartmouth Atlas. I account for the initial wage gap, reimbursement gap, and reimbursement rate gap observed in the data. The initial wage gap between primary care physicians and specialists in the past 5 years is equal to 0.097 log units in cities, 0.020 log units in small cities, and 0.028 log units in rural areas. More details on the estimation are available in the text.