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JEL Classification: L15, J31, J44, I13, I18

Keywords: Competition, inertia, Quality, Returns to skill

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Who benefits when inertia is reduced? Competition, quality and returns to skill in health care markets*

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January 7, 2020

Abstract

Increased competition creates incentives for health-care providers to improve quality by incorporating better inputs, like higher-skill physicians. However, because the supply of high-skill physicians is relatively inelastic in the short run, increases in competition may lead only to increases in returns to skill. I leverage a reform in Uruguay that increased competition among completely vertically integrated providers by reducing lock-in of consumers. Using administrative data on wages and hours and a measure of physicians' skills based on test scores from medical school, I show that increased competition increased the returns to skill without strong evidence of an increase in quality.

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1 Introduction

An increase in competition can have ambiguous effects on quality in a context in which firms can choose both prices and quality. The evidence in the health care sector, mostly focused on the hospital segment, is mixed and more often points towards increased competition having a positive effect on quality (Propper, Burgess, and Green 2004; Gaynor, Ho, and Town 2015). One of the factors behind these mixed results can be differences in the conditions in the markets for the inputs needed to increase quality. The possibility and cost of increasing the utilization of inputs depend on the availability and therefore the elasticity of supply of these inputs, which can be relatively inelastic in health care markets (Cutler, Huckman, and Kolstad 2010). If the input has a very inelastic supply, an increased demand for the input will increase its price without increasing its quantity much. In this case, the potential beneficial effects of competition shocks can be almost totally absorbed by cost increases without improving quality. This is particularly relevant in health care markets, where policies aimed at improving welfare through expansions of coverage or intensification of competition are likely to generate demand shocks for more and better physicians, which have a relatively inelastic supply in the short run given their occupational license requirements, potentially increasing the costs of the system via higher returns to skill.

The goal of this study is to further understand the effects of increased competition on input markets by using a setting that offers a change in competition and a measure of input quality that are plausibly exogenous. I analyze the effects of increased competition on the market for medical specialists in terms of returns to skill and relative hours worked. When providers receive incentives to intensify (non-price) competition, does the relative demand for high-skill physicians increase? If so, do the returns to skill increase? Finally, does this increased relative demand lead to a general increase in the quality of providers? I evaluate whether increased competition shifts the relative demand for high-skill medical specialists and whether, consistent with the idea of an inelastic relative supply in the short run, increases their relative wages without increasing quality, which is approximated as the relative hours of high-skill over lower-skill physicians.

This paper evaluates the impact of increased competition in the context of the Uruguayan health care system, leveraging a change in the lock-in rule for consumers. In 2009, and after nine years of complete lock-in, the government reduced the lock-in of consumers in the public health insurance program by implementing a regulated mobility scheme, which increased competition in the market. In addition to this plausibly exogenous variation in competition, the Uruguayan health care system has two characteristics that provide an excellent setting to identify these effects. First, health care providers in Uruguay are completely vertically integrated, providing each provider the services that insurance companies, hospitals and physician provide in other countries. Providers are not specialized in the treatment of different conditions, and consumers receive all their health care from the provider they are enrolled with. This setting allows for a very clear consumer demand for providers and means that consumers have incentives to care about provider prices and quality when they are making an enrollment decision. Second, physicians are hired by providers and receive wages for their worked hours. Therefore, providers have incentives to demand more hours of high-skill physicians in order to increase their own quality and capture a larger share of the consumers who have increased choice after the reform. Since medical specialists need an occupational license to work, the response of medical specialists to this demand shock in the short run can be very inelastic.[1]

I use administrative records on wages and hours of work in all providers for all physicians with a specialty (specialists hereafter) in the Uruguayan health care system. I combine these administrative records with information on scores in the admissions test for medical specialty graduate school, which I use as an exogenous measure of the quality of specialists. This measure of quality is predetermined and thus exogenous to labor demand responses to changes in the competitive environment. To the best of my knowledge, this paper is the first to use test scores of physicians in a systematic way to understand changes in returns to skills induced by competition shocks. I leverage the fact that up to 2010 only one school offered medical specialty degrees, and I use the test scores for the cohorts of graduate medical school applicants between 1996 and 2010 to analyze the effects of increased competition on their wages and hours of work.

First, I present a simple theoretical framework that discusses the effects of increased competition on returns to skill and relative hours. Intuitively, if the relative supply curve of high-skill specialists is relatively inelastic, the demand shock created by increased competition leads to higher returns to skill. The size of this effect and the increase in relative hours depend on the elasticity of the supply curve. A totally inelastic supply curve in the short-run is consistent with large increases in returns to skill and no increases in quality. In the long run, the supply is less inelastic and therefore we would expect a smaller effect on returns to skill, because of the entrance of new specialists.

[1]In the US, the workforce covered by state-level occupational licensing laws grew dramatically in the second half of the 20th century, going from less than 5% in the 1950s to approximately 30% nowadays (Kleiner and Krueger 2010). The presence of occupational licenses decreases informational asymmetries but can also secure rents for those in the occupation, raising prices and harming low-income consumers especially. With a few exceptions, remarkably (Larsen 2015), little is known about how occupational licenses affect quality.

Then, I provide descriptive evidence to show that, while there was an increase in the wages of all specialists' during the period, the wages of high-skill specialists–those with higher test scores–increased much more than those of low-skill specialists, and the timing of these relative changes encompasses the changes in the lock-in rule. I also discuss how the test scores reflect the quality of specialists by showing that these scores are associated with lower costs for providers, shorter waiting times and higher measures of clinical quality, and that scores correlate with wages before the reform and with other measures of career success for medical specialists.

To formally test the effect of increased competition, I use a strategy that combines the variation across time introduced by the exogenous change in the policy that started in 2009, with the exogenous (to the labor market) cross-sectional measure of specialists quality given by the test scores. The main identification assumption is that unobserved shocks in hours and wages are uncorrelated with both the quality of the specialist and the timing of the reform, after controlling for individual fixed effects and specialty-by-time fixed effects. In other words, I assume parallel trends in the hours and wages of medical specialists of different levels of skill, conditional on specialty, in the absence of the competition shock. In several robustness checks, I also show that the results are robust to controlling for shocks at the provider-by-time level and to including other controls reflecting the increase in public health insurance coverage during those years. Using the same approach, I also discuss the heterogeneity of the results across age and gender, different medical specialties and geographic regions.

Overview of results. My results are consistent with the hypothesis that the change in the regulated mobility regime intensified competition among providers and caused an increase in the demand for high-skill specialists. Consistent with the existence of a relatively inelastic supply of high-skill specialists in the short run, this shock in competition generated a relatively large increase in the returns to skill. According to my preferred estimates, a change in the regulated mobility regime that increases the percentage of consumers able to switch providers from 0% to 60%, causes a relatively large increase of about 1.1 units in the elasticity of wages to scores. In terms of test score points, after the reform the wage premium for a one standard deviation difference in test scores increased by 27 percentage points. These large effects on wages are consistent with an event-study approach and are robust to several controls.

On the other hand, I find only weak evidence of an increase in the relative hours worked by high-skill compared to low-skill specialists. When the full sample of medical specialists is used, the effects on relative hours are smaller than the effects on wages and not statistically significant at a 5% level. The largest estimated effect of the reform on the elasticity of hours worked to the score is 0.45 units, only statistically significant at 10% level. The estimated effect on hours is much smaller and not statistically different from zero in the event study specification, as well as in regressions that include provider-by-time fixed effects or controls for the effect of the market expansion on the relative demand of high-skill specialists. Overall, the evidence does not support the hypothesis of the change in competition causing an increase in the total quality of the system (measured as the relative number of hours worked by higher-skill specialists).

The large and positive effects on relative wages and small effects on relative hours worked by high-skill specialists are consistent with a relatively inelastic supply of high-skill specialists in the short run. However, these results could also be consistent with a backward bending labor supply curve, where specialists with higher worked hours and total earnings respond by decreasing their labor supply due to an income effect. To test this, I estimate a specification where I allow the reform to have differential effects according to the number of hours worked by each specialist before the reform. I find that the point estimates of the effects on hours worked are indeed smaller for those working more hours before the reform, but they are never negative, so they do not support the hypothesis of a backward bending supply curve.

Additionally, the results of the event studies are consistent with the expected effects given a relatively more inelastic supply of high-skill specialists in the short run than in the long run, as new specialists can enter the market. In this sense, the effects on relative wages are higher around the period when the reform was intensified and fade out in the medium term. In terms of heterogeneity, there is no difference in the effects by gender, but older specialists seem to have a higher increase in returns to skill. Specialties with higher barriers to entry seem to have larger effects on wages. The effects on wages are somewhat larger for specialist working at only one provider. Finally, the market of the capital city, where competition incentives are higher, exhibits similar patterns as in the full sample, with a large increase in relative wages (42 percentage points for a one standard deviation difference in test scores) and a lower (and not statistically significant) increase in hours.

Overall, the results underscore that, for competition in the output market to have positive effects on quality or other reallocation effects, it has to be complemented with flexibility in input markets. These results show how potential beneficial effects of competition shocks can be absorbed by cost increases in input markets. Moreover, they highlight the differences between the adoption of capital and human capital inputs, given their different supply-side elasticities. These differences are crucial to understanding the effects of increased competition in markets with occupational licenses and barriers to entry.

Related literature. This paper contributes to the literature that addresses the effects of competition on quality in health care markets. There are no unambiguous theoretical results on the effect of competition on quality when firms choose both price and quality. The outcome depends on the elasticities of demand with respect to quality and price for different consumers and on the nature of competition. The empirical literature on competition and quality in health care markets is for the most part fairly recent and has grown very rapidly (Gaynor, Ho, and Town 2015). Most frequently, this literature relates a measure of quality (typically mortality rates) to a measure of market structure, and identification comes from the use of exogenous changes in market structure. When prices are administered, the empirical evidence suggests that increased competition increases the quality of hospitals (Kessler and McClellan 2000; Tay 2003; Cooper et al. 2011; Gaynor, Moreno-Serra, and Propper 2013; Bloom et al. 2015; Gaynor, Propper, and Seiler 2016). When prices are market-determined, the results are more mixed, but in general the evidence points to increases in competition improving hospital quality (Ho and Hamilton 2000; Volpp et al. 2003; Propper, Burgess, and Green 2004; Capps 2005). This paper makes a novel contribution to this literature by focusing on a specific and relevant channel through which providers can try to increase their quality in response to increased competition, namely the demand for a key input in production (physician quality). My analysis is similar in spirit to that of Cutler, Huckman, and Kolstad 2010, who analyze an increase in hospital competition via new entry and its effects on the demand for high-quality physicians.[2] Instead of looking at the allocation of patients across specialists, in this paper I analyze the main variables of the market of physicians and highlight the effects that an increase in the demand for quality has on returns to skill and costs.[3] Therefore, this paper underscores the relevance of the functioning and regulations of physician labor markets in shaping the effects of health care market reforms on health care quality and costs and the distribution of rents. It also underscores the difference between short-run and long-run responses of costs and quality with respect to an increase in competition.

This paper also contributes to the literature that aims to understand the welfare effects of reductions

[2]Cutler, Huckman, and Kolstad 2010 study how the entry of hospitals into the coronary artery bypass graft (CABG) surgery market in Pennsylvania affected the quantity and quality of CABG surgeries. They underscore that cardiac surgeons are a scarce input (supply cannot be easily altered), and thus increased market entry does not lead to an increase in the quantity of CABG surgeries. However, they find that new entry increases the quality of surgeries by increasing their allocation to high-skill physicians. They use the *share of high-quality surgeons* as a measure of hospital quality, where surgeon quality is measured using data on risk-adjusted, in-hospital mortality of their CABG patients, which must be adjusted by observable patient characteristics that could affect a patient's underlying probability of dying.

[3]There is also a branch of literature that has studied the effects of health care reforms (expansions) on physician earnings. Finkelstein 2007 studies the effects of the introduction of Medicare on the payrolls of nurses and technicians. Dunn and Shapiro 2014 find that physician payments increased at least 10.8% in counties affected by the Massachusetts reform compared to control areas. Finally, Buchmueller, Orzol, and Shore-Sheppard 2015 find that both the total number of visits to dentists and dentists' income increase when states add dental benefits to adult Medicaid coverage.

in consumer inertia and expansions of consumer choice in health care markets. The presence of significant consumer inertia in health care markets has been well established; recent research, policy debates and news have suggested policies to reduce inertia in these markets. A recent stream of literature has analyzed the effects of inertia and other choice inconsistencies in health care markets, and most of this research analyzes possible reductions of inertia (Abaluck and Gruber 2011; Ketcham et al. 2012; Abaluck and Gruber 2016; Heiss et al. 2013).[4] This paper underscores how reductions of inertia or expansions of consumer choices can increase costs, potentially not leading to increased consumer welfare, by pushing the demand for an inelastic input.

Finally, this paper is also related to a literature that discusses the extent to which an intensification of competition affects returns to skill and wage inequality. Increased competition can lead to changes in rent sharing or union behavior (Rose 1987; Hirsch 1993; Card 1996) or to changes in the technology of production (Aghion et al. 2005; Acemoglu, Aghion, and Violante 2001). A more direct effect comes from the fact that more competition can cause more efficient firms to capture a larger share of production (Boone 2000; Vives 2008), and therefore the relative marginal product between two given skill levels increases, returns to skill rise, and so does wage inequality (Guadalupe 2007; Cuñat and Guadalupe 2009). This paper contributes to this literature by using individual level administrative records and plausible exogenous variation to analyze a sector of the economy where there are occupational licenses and where changes in returns to skill caused by increased competition and the resulting effects on quality have very relevant policy implications in terms of costs and quality of life.

The remainder of the paper is organized as follows. Section 2 presents the institutional framework. Section 3 presents the theoretical framework. Section 4 presents the data and descriptive statistics. Section 5 describes the empirical approach. Section 6 discusses the results and a series of robustness checks. Section 7 concludes.

2 Background

The Uruguayan health care sector offers a relatively clean setting to understand the effects of competition on quality and physician wages and hours. This section presents the key characteristics of the

[4]This literature also include Handel 2013 and Polyakova 2016, who analyze its interactions with adverse selection; and Ho, Hogan, and Scott Morton 2017, who discuss the relative importance of inattention and switching costs as sources of consumer inertia. Moreover, a recent body of empirical work assesses the effects of inertia on strategic pricing behavior in Medicare Part D (Ericson 2014; Ho, Hogan, and Scott Morton 2017; Miller 2014; Fleitas 2017).

Uruguayan public health insurance system (FONASA),[5] and briefly discuss the main factors that are fundamental to the empirical strategy followed in this paper. FONASA is a public health insurance policy that aims at providing universal coverage to the population. With the goal of universalizing coverage, in July 2007 FONASA started covering everyone who was previously covered by the social security program (DISSE) plus the public sector workers who had no other source of coverage. From then on, FONASA gradually incorporated different groups of individuals, including workers in the banking sector, notaries, retirees, and dependent children and partners of other individuals covered by FONASA, totaling about two thirds of the population by 2013.

Once covered by FONASA, a person has the right to choose a health care provider among the public health care provider (ASSE) and private providers. For each person covered, FONASA pays an age- and gender-adjusted per capita monthly fee to the provider. The amount of the fee is fixed by the regulator and is the same for every health care provider. Consumers make contributions to FONASA via tax contributions on earnings that do not depend on whether they choose ASSE or any private provider. Therefore, under FONASA, the out-of-pocket costs are the only differential cost for consumers when choosing a provider and the most important factor in their decisions. When deciding about enrollment, consumers also care about the quality of the providers, represented mainly by the waiting times and the quality of the physicians working in the different providers. When not covered by FONASA, consumers can pay a premium and enroll in the provider of their choice or can use the public health care services (ASSE). In this sense, almost all new FONASA consumers are consumers who were previously privately enrolled in a provider or receiving health care services from ASSE (non-FONASA ASSE consumers hereafter).

Although the government has been carrying out a plan to increase the quality (and budget) of the public health care services, most of the population see ASSE as a lower-quality health care provider than private providers, and the majority of consumers in FONASA (87%) choose to enroll in the latter. There are 38 providers in Uruguay, with 11 in the capital city. According to the Uruguayan Department of Health, the other providers are distributed in 16 markets, which in general correspond to the departments (*departamentos*).

Providers in Uruguay are vertically integrated, being both the insurance company and the direct

[5] Uruguay has a population of 3.3 million and a GDP per capita of about 16,000 USD in PPP in 2012 (Uruguay is similar in population and size to the state of Oklahoma in the United States, and the GDP per capita of the US is approximately 3.25 times as large). Health expenditures represented around 9% of the GDP in 2012. The Uruguayan population is relatively elderly and has relatively high life expectancy at birth (77 years), with population dynamics in terms of mortality and birth rates similar to developed countries. Most of the population (95%) lives in urban areas, with 40% of the total population living in Montevideo, the capital city.

providers of health care. In this sense, and contrary to what happens in many countries and, remarkably, the US, there is a direct demand for providers of health care services. There are no insurance companies intermediating between consumers and these providers. Moreover, physicians are hired by these providers and receive wages for their worked hours. Therefore, consumers consider the characteristics of the providers (out-of-pocket prices, quality and waiting times) in order to choose among them. Second, each person receives all the health care services from the provider they choose to enroll with for the time of the lock-in period. An important consequence of this fact is that providers are not specialized in different health conditions or medical specialties.

From the providers' point of view, most of their revenues come from the monthly fees (an analog to premiums) paid by FONASA. Other sources of revenues are the out-of-pocket expenditures that consumers have to pay for doctor visits, clinical studies and other treatments, which represent a significant share (9% in 2011) of the total revenues of providers. Price increases of these copayments are regulated, but their relative prices are determined by provider competition.

In addition to out-of-pocket price competition, consumers care about the quality and the availability of physicians in these institutions, and in particular about the waiting times for appointments with professionals of certain medical specialties. Since 2009, the Department of Public Health releases some information about out-of-pocket prices, the accomplishment of some goals set by the regulator, and other general information, with the purpose of making consumers' decisions more information-based. However, the information provided is still not consistent and has been changing over the years; thus it is impossible to construct consistent data series.[6] Providers have very little room to use other potential drivers of competition because of the regulation. The incorporation of technology to play an "arms race" is prevented by a tight regulation of requirements that health care organizations must satisfy to incorporate new technology. As part of these requirements, the regulator evaluates the perceived demand in the system and the impact of the technology on consumers' health. Advertising also has tight regulations and was increasingly regulated during the reform period. For example, since December 2011, the regulator informs providers about the priorities that advertisements should address, and no less than 80% of the total time of the advertisement must be about those contents.[7]

Competition in the quality of physicians is very important in the system. For example, anecdotal evidence indicates that waiting times are usually longer for appointments with better specialists, which

[6]In Section 4, I use the information available to show the validity of my quality measure of physicians.

[7]In 2014, and after the period of this study, a court ruling determined that advertisement should be allowed, and expenditures in advertising increased significantly.

suggests a "willingness to pay" for physician quality, particularly for specialists. Also, consumers typically talk about the "quality" of physicians; in particular, since the most renowned physicians usually also work in the public university, their positions at the university (as assistant, associate or full professor) are typically mentioned in these conversations. However, a position at the university is not an exogenous measure of quality of physicians, since it can be affected by the provider where they work and other factors. To construct an exogenous measure of the quality of specialists, I leverage the fact that physicians must take a test to be admitted into the graduate school to train for a medical specialty. Moreover, these test scores are comparable, since until 2014 only the public university, Universidad de la República, offered medical specializations. Therefore, the scores in this test can be used as an exogenous measure of quality of the specialists.

Physicians in Uruguay must complete a training period of 8.5 years to receive a degree as a non-specialized medical doctor. After that, those who want to pursue graduate studies in a specialty must undertake about 4 more years of medical training. To enroll for this specialization training, they must obtain a minimum score in an exam. Since 1984, those who have obtained the best scores have received fellowships during their studies (they get paid during the length of their residencies). The other students can access the same education but are not paid, and they usually have other jobs while studying. By compiling and digitalizing administrative records from the public university, I collected exam scores for the cohorts of graduate medical school applicants between 1996 and 2010. This score is the measure of quality of specialists that I use in my empirical approach.

In this paper, I also leverage the changes in consumer lock-in rules that started in 2009, and the effects that these changes had on the competition among providers, to identify the effects on wages, hours and overall quality of providers. In 2009, the government instrumented an open enrollment period for the first time in nine years, during which each person covered by FONASA was allowed to switch to another provider. Before that, there was a period of nine years during which each individual who received coverage through the social security health insurance program (FONASA, and formerly DISSE) was locked-in with the same provider they had at the time the lock-in policy was implemented in 2000, or when they started contributing to social security, whichever happened later.[8] In 2009, this regime changed, and Act 65/009 established that the persons covered by FONASA would be allowed to switch to another provider in the system during February 2009 if by February 1st, 2009 they had been enrolled

[8]The reason declared by the government for this regulation was the fact that some providers were "buying" consumers, paying them to switch providers, but the implementation of the policy was contemporaneous with severe macroeconomic instability associated to a banking crisis.

with the same provider for at least 10 years. The act also established that once a person switched to another provider, they would have to remain enrolled at the new provider for at least three years before being able to switch again.[9] New legislation in 2010 and 2011 further reduced the requirements for being allowed to switch providers, effectively increasing the number of people who were allowed to switch.[10] By 2011, all FONASA beneficiaries that had been enrolled with the same provider for at least three years would be allowed to switch providers in each open enrollment period.

To summarize, I use the changes in the lock-in rules as a quasi-experiment by leveraging three facts: a) health care providers are completly vertically integrated, providing at the same time the insurance companies services and the physicians and hospital services; b) until 2014, only one university could issue specialist degrees, students had to take a test to gain admission and I use these test scores as a measure of specialist quality; and c) an exogenous increase in competition started in 2009 due to a reform of the lock-in rule for consumers who were unable to switch providers before.

3 Theoretical Framework

In this section I begin by describing how the relative wages and hours of higher skill specialists relative to those of lower skill specialists are set in a market with the characteristics of the one described in the previous section. I follow and expand to the case of two skills a simple model presented in the literature (Nicholson and Propper 2011; Nicholson 2008) to understand both the short-run and long-run effects. While this section does not present a formalized model that incorporates all the frictions potentially present in this market, it provides a simple and clear theoretical foundation that guides the empirical analysis detailed in the next section.

3.1 Relative supply and demand of specialists

Let us first focus on the relative supply of specialists and afterwards on the relative demand. From now on, and for simplicity of the language, I refer to the relative supply (demand) of high skill physicians compared to that of low skill physicians as the relative supply (demand).

[9] The Act established that the individuals who were assigned to ASSE by default (because they did not choose a provider when they obtained FONASA coverage) would be allowed to choose a provider in February each year.

[10] In 2010, Act 14/010 established very similar conditions to Act 65/009. However, the requirement for being able to choose a new provider was reduced to seven years instead of 10 years of being enrolled with the same provider. In January 2011, Act 03/2011 further reduced the requirement for switching providers for individuals covered by FONASA, establishing that individuals with at least three years of enrollment with the same provider would be able to switch providers during the open enrollment period of each February. In both cases, the requirement of the lock-in for the next three years after switching providers was kept unchanged, and people assigned to ASSE by default could also change under the same conditions.

Long-run relative aggregate supply of specialists. The total number of relative hours of work high quality specialists are willing to provide depends on how many high skill specialists relative to low skill specialists chose to enter the profession in the past, and how many hours each high-skill specialist decides to work compared to low-skill specialists. Assume, for simplicity, that there is only one specialization available to medical graduates, either they do a specialty or the stay as general physicians. Medical school graduates derive utility from consumption and the non-monetary attributes of a specialty. Some examples of non-monetary attributes include prestige, the intellectual content of the specialty, the types of patients and colleagues one interacts with, and the flexibility of the work schedule.

Assume there are two types of physicians, high skill (HS) and low skill (LS), indexed by i, therefore $i \in \{HS, LS\}$. The expected lifetime difference in earnings and non-monetary attributes, net of all costs of the required graduate education, between specialty (S) and staying as a general physician (G) is defined as $\Delta Y^i = (Y_S^i - Y_G^i)$. The equalizing difference, denoted as Z^i, is the additional earnings that a medical graduate must receive in the specialty in order to be exactly indifferent between entering the two occupations, and it can be positive or negative. A physician will pursue the specialty if the earnings difference between the specialty and being a general physician (ΔY^i) exceeds the skill-specific individual equalizing difference (Z^i); otherwise, she will choose to stay as a general physician. In equilibrium, all those selecting the specialty will have a ΔY^i that exceeds their Z^i, and all those selecting general physician will have a ΔY^i that falls short of their Z^i.

In this model, the ratio of high-skill relative to low-skill medical graduates entering the specialty is increasing with the relative net expected lifetime earnings and non-monetary attributes of high-skill relative to low-skill specialists: $\Delta P = \frac{\Delta Y^{HS}}{\Delta Y^{LS}} = \frac{(Y_S^{HS} - Y_G^{HS})}{(Y_S^{LS} - Y_G^{LS})}$. Therefore, other things constant, an increase in the skill premium for high-skill specialists will increase the aggregate relative long-run supply. How many more high-skill relative to low-skill graduates would choose to become specialists because of an increase in returns to skill in the specialty? First, in the margin between general physician and a specialist, it will depend on how many high-skill students have an equalizing difference close to ΔP. The distribution of equalizing differences could have any shape. If there are many high-skill medical graduates with a value of Z^{HS} close to ΔY^{HS}, then many more high-skill students will choose the specialty over being a general physician when the expected returns to skill for specialists rise, other things constant. In this scenario, the aggregate relative long-run labor supply curve will be more elastic.

A second channel is that more high-skill students will decide to be general physicians compared to other professions, given the possibility of continuing their education later on and becoming specialists.

The skill mix of the physician workforce changes slowly over time because the flow of newly trained high-skilled physicians from residency training is small relative to the stock of specialists. In practice, skills composition and long-run supply may be dictated by the ratio of skills in the pool of applicants to study medicine and the availability of residency positions.

Short-run relative aggregate supply of specialists. The short-run aggregate relative labor supply will be steeper than long-run aggregate relative labor supply due to the length of required medical training for specialists and other potential barriers that can delay entry. In general, high-skill specialists will supply relatively weakly more hours in the short run if the skill premium increases, as high skill specialists who are already trained and practicing in a market decide to work longer hours. Note that, if the aggregate relative supply of specialist is completely inelastic, the number of relative hours is fixed for any level of skill premium.

One additional element in this setting is the possibility that the relative supply of specialists in the short run may be backward bending, that is, that an increase in returns to skill would lead to a reduction in the aggregate relative supply at least for some specialists. The shape of the short-run relative aggregate labor supply curve depends on the relative magnitudes of the income and substitution effects for each type of specialist. When the skill premium increases, high-skill specialists have incentives to work more (*substitution effect*) since now leisure is more expensive. However, at the same time, high-skill specialists become relatively richer, and therefore have incentives to work fewer hours (*income effect*). The relative strengths of these two effects for high-skill and low-skill specialists determines if the short-run relative supply curve is backward bending.

While the classic studies in this literature find evidence consistent with backward bending labor supply, the physician labor supply literature, especially recent papers, finds evidence of standard upward-sloping labor supply.[11] McGuire and Pauly 1991 discuss the possibility of targeting effects when changes to payments for specialists are introduced. The idea is that physicians may have income targets and they may increase the quantity of patients by inducing demand if they face payment changes. This would also create changes in the elasticity of supply in the short run. On the other hand, Clemens, Gottlieb, and Hicks 2018 use variation in Medicare reimbursement rates for surgeons relative to other physicians and show that patient care hours respond negatively to prices, while on-the-job investments respond positively, suggesting that seemingly backward-bending labor supply can be driven by on-the-job invest-

[11] See McGuire 2000 and Chandra, Cutler, and Song 2011 for a review of the literature on backward bending labor supply. Recent literature on physician labor supply has found evidence of upward-sloping labor supply (Clemens and Gottlieb 2014; Johnson and Rehavi 2016; Brekke et al. 2017; Foo, Lee, and Fong 2017).

ment dynamics, rather than income targeting. I discuss the evidence on backward-bending behavior in my setting in Section 6.

Providers' relative demand for specialists. Let us now turn to the demand for specialists. Providers hire high-skill and low-skill specialist hours as production factors into a productive process. These two factors are imperfect substitutes. Providers may have at least two reasons to hire a higher ratio of high-skill specialist hours in their total hours of specialists. First, a higher ratio of high-skill to low-skill hours is perceived as quality by the consumers and, in turn, it affects their decision of enroll with the provider and the prices of out-of-pocket expenditures, since these consumers have some willingness to pay for quality. Therefore, a higher ratio of high-skill specialists can increase the revenues of these providers. Second, a higher ratio of high-skill to low-skills hours can generate cost savings to the providers if high-skill specialists can reduce the cost of different treatments. Examples of this would be that higher-skill specialists are able to detect conditions early or diagnose without over-intensive use of diagnosis devices. In this case, higher-skill specialists will reduce the cost of the provider. In equilibrium, these additional profits for having a high-skill specialist equal the additional cost of hiring a high skill specialist. Therefore, the larger the relative wage of high-skill to low-skill specialists, the smaller the relative demand for high-skill specialist hours.

3.2 Short and long run equilibria under intensified competition

Effect of intensified competition on demand. Now consider a reduction in consumer inertia in the product market, created by the change in the lock-in rule. After the change, consumers can choose their optimal provider and switch more often, increasing the level of competition in the product market. The increased competition in the product market may create in turn and increase in the relative marginal product of high-skill specialists. As mentioned before, high-skill individuals can increase profits either because they attract consumers, allow providers to increase out-of-pocket prices, or because they reduce costs. If these channels become more valuable when the product market is more competitive, the intensified competition will create a shift outward in the relative demand for high-skill specialists. These channels from intensified competition to returns to skill have also been discussed in models for other sectors of the economy in previous literature (Guadalupe 2007; Boone 2000; Vives 2008).

Short-run equilibrium. The shift outward in the relative demand generates changes in the relative wages and relative hours in both the short and the long run. Relative wages and relative quantity of hours will rise in the short run. A key point here is that the more inelastic the relative aggregate supply of high-skill specialists in the short run, the larger the increase in relative wages and the smaller the increase in relative hours. For example, if the relative aggregate supply of high-skill specialists in the short run is completely inelastic, then we will observe large increases in relative wages (skill premium) and no effect on relative hours. As mentioned before, the aggregate labor supply in the short run can also be backward bending. In this case, following an increase in relative wages, we will observe an increase in relative hours in some part of the relative supply curve and a decrease in relative hours in other parts of the relative supply curve. Additionally, we can also observe an increase in relative wages and no increase in relative hours if the income and substitution effects perfectly offset each other.

Long-run equilibrium. In the long-run, more high-skill medicine graduates will decide to enter the specialty, now that the skill premium has increased (and also overall more people will study medicine). The path to the adjustment to the long-run equilibrium depends on the expectations of individuals. If they have static or "cobweb" expectations, they will expect the skill premium to remain permanently at the level of the short-run equilibrium. In this case, supply will increase substantially in the long run, thereby creating a surplus of high-skill specialists, a subsequent reduction of the flow of specialists as the relative wage falls, and endless cycles of surpluses and shortages. On the other hand, if individuals have rational expectations, they will adjust directly to the equilibrium.

Overall, the intensification of competition, driven by the change in the lock-in rule, should generate an increase in the demand for high-skill specialists. In the short-run, we expect this shock to increase the relative wages and potentially (if the aggregate supply is not totally inelastic) relative hours. In the long run, the entry of new high-skill specialists will reduce the effects of the shock on returns to skill. In this paper, I use a shock to relative demand for high-skill specialists to estimate its effects on relative hours and skill premium, which depends on the short-run elasticity of relative supply. In the event study specification, I also discuss how this short-run equilibrium converges to a new long-run equilibrium.

4 Data and Descriptive Statistics

4.1 Data sources

I use three main sources of data. The first one is the SCARH, an administrative database from the Uruguayan Department of Health, which has hours worked and wages for each medical specialist in Uruguay. This dataset is at the medical specialist and quarter level and spans the period from the second quarter of 2007 to the second quarter of 2014. Note that this period covers the change in the lock-in rule

(2009). The data also contain information about medical specialty, gender, age and provider(s) where each medical specialist works.

The second source of data is a database with the test scores that physicians obtained in the entry exam for the medical graduate school training to become specialists. Until 2014, in Uruguay there was only one medical school were physicians could train for their specialty. Therefore, this allows me to have tests scores for the whole cohort of new specialists by year, which are comparable across cohorts and individuals within a cohort. To the best of my knowledge, this is the first time that medical graduate school test scores have been used to measure quality in the literature of health care economics. I obtained and digitalized data on 1197 medical specialists, which cover the cohorts that took the exam between 1996 and 2010 and represent about 22% of the total stock of medical specialists in Uruguay. Different specialties have different exams, but all exams are graded over 40 points (with a minimum passing score of 20 points).

Third, I use an additional source of data that refers to the regulated mobility regime and includes the total number of FONASA beneficiaries, the number beneficiaries able to switch providers during each open enrollment period, and the number of beneficiaries that decide to switch in each year. This information is available at the website of the Department of Public Health. Table 1 shows the evolution of these variables in the period 2007 to 2014. The number of people covered by FONASA increased over time, from about 754 thousand in 2007 to about 2.3 million at the end of the period. These new FONASA consumers are a combination of individuals who were previously privately enrolled with the providers paying the premium, or consumers who were enrolled with ASSE (non-FONASA ASSE consumers).

4.2 Descriptive statistics

The descriptive statistics for specialists are presented in Table 2. The first three columns present the information about the population of specialists in Uruguay reported in the SCARH database (5401 specialists), while the other three columns present information about the sample of those for whom I have information on scores (1197 specialists). The average age of specialists in Uruguay is 46 years old. Since I have scores only for exams between 1996 and 2010, the average age in my sample is 35 years old, which is considerably lower. I discuss the role of age in Section 6. Regarding gender, specialists in Uruguay tend to be female (62%) and this situation is even clearer in my sample, where 70% of specialists are women. For the same reason of being younger and having less experience, the specialists in my sample work fewer hours (123 vs. 166 hours per month) and have lower wages per hour (16 vs.

29 dollars per hour) compared to the population of specialists in Uruguay. The population of specialists also has higher standard deviations in wages per hour and hours worked. Some specialists receive very high wages per hour and also report working a very high number of hours per month, because providers compute on-call hours as hours worked. Figure A.2 in online Appendix A, shows histograms of the distribution of wages per hour and hours worked for the population and the sample. Finally, the average score in the exam for the sample is approximately 27 with a standard deviation of 7 points.

Specialists in Uruguay sometimes work for more than one provider at a time. About 65% of total specialists worked at only one provider at a time, while the other 35% worked at two or more providers for at least one period. In the sample used in this paper, the distribution is very similar, with 69% of specialists working at only one provider during each period of time. When we compare the descriptive statistics for these two groups, the specialists who work at one provider at a time are very similar in characteristics to the other specialists, and this similarity is true for both the population of specialists and the sample. Some differences can be found in wages per hour and in hours worked. While in the full population specialists who work at more than one provider have relatively lower wages per hour and work fewer hours, in my sample these differences are somewhat reversed. However, the differences are relatively small and are consistent with the best specialists working at only one provider as their careers develop.

4.3 Scores as a measure of skills

In this subsection, I discuss and evaluate to what extent test scores in specialty entry exams are a good proxy of skill of the specialists and quality of the providers. I use the scores from the exam that medical doctors take in order to obtain admission to a specialty training, before starting their professional careers as physicians or specialists. This is a high stakes exam for which individuals prepare and exert effort. Therefore, their scores reveal some intrinsic skill of the individual that is exogenous to their labor market experience. I begin by discussing previous literature that has used test scores as a signal of quality and to understand how skill is used and learned in the labor market. I then present evidence showing that my measure of skill is associated with characteristics that providers and consumers care about, such as lower costs, shorter waiting times, and higher clinical quality.

The choice of using test scores as a measure of skill of medicine graduates is consistent with a literature that finds that university graduation plays a direct role in revealing ability to the labor market. For example, using the Armed Forces Qualification Test (AFQT) as a measure of ability, Arcidiacono, Bayer, and Hizmo (2010) find evidence that college graduates are paid in accordance to their own ability immediately upon entering the labor market, while it takes longer for the market to reward the ability of non-college graduates.[12] This is consistent with the fact that a number of factors contribute to ability revelation: resumes of recent college graduates typically include information on grades, majors, standardized test scores, and the university from which the individual graduated. The latter has also been used as a proxy of quality of physicians in the literature (Schnell and Currie 2018).

The limited measures of quality and costs of providers available in this setting, provide validation to the use of these test scores as a proxy for skills. A first piece of evidence comes from analyzing the correlation between the scores and pre-reform wages of specialists, by regressing log pre-reform wages on the test scores of specialists. The hypothesis is that, if higher scores are a good proxy for skill, specialists with higher scores will have higher productivity and thus higher wages. While I cannot estimate the causal effect of an increase in the score on wages because the score may be correlated with other characteristics of specialists and their employers, regressing wages on scores allows me to obtain an estimate of the association between them. I conduct estimations with time fixed effects, and with and without specialty fixed effects, using alternatively log score and score. Note that it is not possible to to include individual fixed effects. The results are presented in online Appendix A, Table A.1. In all specifications, there is a strong and positive correlation between wages and (log and levels of) scores. In the specification with specialty fixed effects, the elasticity of wages to scores is 0.69 (regression over log score), and one extra score point is associated with 2.8% higher wages (regression over score in levels).

The second piece of evidence comes from testing the correlation between scores and the placement of specialists as professors and assistants in the public university where physicians study medicine and specialties.[13] In order to explore this, I obtained the directory of all professors and research and teaching assistants at Universidad de la República's School of Medicine, and I checked their test scores. Because I am working with cohorts that graduated after 1996, many of the specialists in this sample are in the first stages of their academic careers (teaching and research assistant positions, which in this university are not associated with being a graduate student), and those that are professors mainly hold positions of assistant and associate professors. I find that the individuals who enter academic careers obtained an average test score of 34 points, which is above the average of 27 points for the full sample.

[12]There is some evidence of learning about skills over time (Arcidiacono et al. 2016; Bobba and Frisancho 2016; Jacob and Rothstein 2016). However, learning over time about productivity happens more among low productivity than high-productivity workers like medical specialists (Lange 2007; Kahn and Lange 2014; Craig 2018).

[13]As discussed, working for the university does not preclude from also working for private providers, and most university professors are also employed by private providers.

The third piece of evidence consists of showing that my measure of specialist skill is correlated with lower provider costs per enrollee, shorter waiting times, and other measures related to clinical quality of their enrollees. I regress the available information of provider quality and costs, on a measure of quality by provider, computed as the log of the average score of all specialists employed by each provider for whom I have information. There are two limitations that come from aggregating the analysis from the specialist level to the level of the provider. First, the number of observations is reduced, since there are only a few providers in the setting. Second, there can be attenuation bias from measurement error, since I only have information on younger cohorts of specialists and not on the total number of specialist employed by each provider. Unfortunately, there is no systematic information on the quality of the providers collected by the regulator. I use the information available from three different sources. First, I collect information about cost per enrollee, made available by the regulator annually from 2007 to 2011. Using a regression model with provider fixed effects, I find that the cost per enrollee decreases with the measure of quality of providers based on specialists test scores. These results are shown in Table A.2 in online Appendix A, in Column I of Panel A. Second, I evaluate waiting times by provider for all specialists, and for pediatrics, gynecology, and cardiology, reported by the regulator from a survey to consumers in 2010. Columns II to V of Panel A, show that waiting times are negatively correlated with the average quality of the providers. Finally, in Panel B, I show that the average quality by provider is positively correlated with higher clinical quality, using the information by provider obtained from the regulator for years 2007 and 2011. The results indicate that a higher proportion of high-skill specialists is associated with a lower rate of hospital readmissions, a lower ratio of C-sections, earlier pregnancy detection and controls, a higher ratio of non-urgent to urgent admissions, and a higher ratio of inpatient visits to urgent admissions (although the latter two are not statistically significant).

Finally, the fourth piece of evidence comes from analyzing if the decisions of individuals in terms of choosing providers are correlated with my measure of quality at the provider level. In Table A.3 in online Appendix A, I find a strong and positive correlation between the log number of enrollees and the average quality of providers, measured as explained in the previous paragraph. The results show that the correlation is positive (and statistically significant) even when including provider fixed effects, time fixed effects and an index of out-of-pocket prices charged by each provider. This correlation between market share and my measure of quality based on test scores is consistent with the idea that consumers choose a provider with higher quality.

Overall, the measure of specialist skill used in this paper comes from a high stakes exam that reflects information about future specialists that are already graduated as physicians but have not yet entered the labor market. It is important to note that a contemporaneous measure of quality of the specialist would introduce endogeneity, because it could be correlated with provider factors, for example related to on-the-job training.[14] I show that my measure of skill is correlated with higher wages before the reform, with higher probabilities of becoming a university professor, and lower costs per enrollee, shorter waiting times, higher clinical quality and higher market shares of providers. Therefore, higher-skill specialists are associated with reduced costs and increased demand for and quality of providers, in ways that are easily understandable by the consumers, such as lower waiting times.

4.4 Regulated mobility, competition and returns to skill

As mentioned above, mobility was prohibited from 2000 to 2008 under the social security health insurance system, and around 2011 the percent of people able to switch providers peaked. In my empirical approach, I use the percentage of people covered by FONASA who are able to switch, in order to identify the intensity of the competition. As discussed in Section 2, in 2009 only those who had been enrolled with the same provider for at least ten years were allowed to switch, which represented 424,000 people (28.4%). In 2010, the requirement was lowered to having been enrolled with the same provider for at least seven years, and therefore the number of people able to switch increased to 528,000 (34%) that year. From 2011 on, the requirement for being able to switch during each open enrollment period was to have been enrolled with the same provider for the last three years, which represented about 1.2 million people (around 60%) per year (Panel (a) in Figure 1). Of those beneficiaries able to switch, not everyone actually switched providers. The number of people switching providers was higher during the first years after the reform, reaching a maximum of 159,000 people in 2011 and staying stable around 77,000 on average during the last years of the sample period.

The implementation of the regulated mobility scheme generated more incentives for firms to compete. Each year, many beneficiaries were able to choose a new provider after being locked-in at one provider for a long time. A way to check the existence of increased competition is to check the evolution of out-of-pocket prices. Fleitas 2016 computes a price index of out-of-pocket prices for providers from the first quarter of 2009 to the second quarter of 2013. Panel (b) in Figure 1 shows the evolution of this price index for a sample of the five highest-price providers in the capital city. The graph shows that, at

[14]Unfortunately, in this paper I have no reliable measure of contemporaneous quality of specialists. With such a measure at hand, it would be possible to use the test scores as an instrument for contemporaneous quality of the specialists in a two-stage least squares strategy to estimate the effect of increased competition on the returns to skills and relative hours by skill.

the same time as the regulated mobility regime was modified to allow many more consumers to switch providers in 2011, the out-of-pocket prices responded with some providers decreasing their prices and other providers moving to a better relative position and increasing their out-of-pocket prices. One limitation of this information is that, since it starts in 2009, it does not allow us to check the evolution of prices before and after the first change that allowed beneficiaries to switch providers. Although this evolution is not proof of the increased competition, the fact that changes in prices correlate with the changes in the regulated mobility regime suggest changes in the competitive nature of the industry around this time. Unfortunately, information about the magnitudes of provider expenditures on advertising and investments is not available, although these are heavily regulated.

Additionally, an important fact for the identification strategy described in the next section is that, since consumers must receive all their health care from the provider they are enrolled with, providers in Uruguay are not specialized. This fact is true even in the market of Montevideo, which has the largest number of providers. Figure A.1 in Appendix A shows the distribution of visits to the providers of Montevideo for the year 2012, suggesting that no systematic specialization exists in terms of the treatment of different conditions across providers.

To motivate the empirical approach discussed in the next section, Figure 2 presents raw data on the differential evolution of the wages per hour of high-skill and low-skill specialists. I start by computing the percentile of the distribution of scores where the specialists are. Panels (a) and (b) of Figure 2 present the evolution of the average log wages per hour over time for the specialists in the top and bottom 10% and 30% of the distribution of scores, respectively. These graphs show that before 2009, the evolution of log wages per hour was relatively similar, but that after 2009 (and especially around 2011) the wages of high-skill specialists increased more than the wages of low-skill specialists. Although this descriptive evidence is clearly in line with the hypothesis that the increased competition had a causal effect on returns to skill, other factors could have affected this comparison. The next section presents the empirical approach and the identification strategy that allows me to establish the causal effect of increased competition on returns to skill and relative hours of high-skill specialists.

5 Empirical Approach

The theoretical model suggests that wage offers are a function of the skill of the medical specialist, the level of competition and other factors like the technology of the firm and other individual level factors. On the empirical side, the strategy is to exploit two sources of exogenous variation: a) the baseline skill of specialists measured by tests scores, interacted with b) a change in the lock-in rule in the product market that incentivizes competition among vertically integrated providers. The specification to be estimated with the data is as follows:

$$\text{Log(y)}_{ikt} \quad = \quad \underbrace{\alpha_{ik} + \gamma_1 \begin{bmatrix} \text{Score} \\ \text{Variable} \end{bmatrix}_{ik}}_{\tilde{\alpha}_{ik}} \underbrace{+ \gamma_2 \begin{bmatrix} \text{Reform} \\ \text{Intensity} \end{bmatrix}_t + \tau_{kt}}_{\tilde{\tau}_{kt}} + \beta \begin{bmatrix} \text{Score} \\ \text{Variable} \end{bmatrix}_{ik} \times \begin{bmatrix} \text{Reform} \\ \text{Intensity} \end{bmatrix}_t + X_{ikt}\theta + \epsilon_{ikt} \tag{1}$$

where i stands for individual, k for specialty and t for the period; Log(y)_{ikt} is, alternatively, log wages per hour or log hours worked; Score Variable_{ik} is the score obtained in the exam by individual i to be admitted in his/her specialization k (in levels or logs); Reform Intensity_t is the share of consumers that are able to switch providers in quarter t; τ_{kt} is a set of dummies for time-by-specialty fixed effects; X_{ikt} is a matrix of control variables (age and age squared); and ϵ_{ikt} is an i.i.d. idiosyncratic shock for specialist, specialty and time. Unfortunately, I cannot separately identify α_{ik} andγ_1, or γ_2 and τ_{kt}. Then, I estimate $\tilde{\alpha}_{ik}$ which is the combined effect of the individual fixed effect plus the effect of the level of skill of the individual, and $\tilde{\tau}_{kt}$ which is the combined effect of the time-by-specialty fixed effect plus the effect of the intensity of the reform. In this equation, β is the main coefficient of interest, representing the effect of the increased in competition on the relative log wages or hours.

A different way to capture the effect of the intensity of competition on returns to skills and relative hours is to non-parametrically estimate the effect of the score variable by year. The specification is very similar to Equation 1, but now the main variable of interest is replaced by a sum of effects by year. Note, however, that the interpretation of the coefficients β_t is different from the β in the previous specification. In this specification, the effect is allowed to vary non-parametrically for each year, to capture in an event study the effects of the reform intensity over the years. In the empirical part I discuss the evolution of these β_t over time and what it can inform about short- and long-run effects.

A third possibility is to estimate the average effect of the reform, by estimating the effect of the score variable interacted with a dummy for the period after the first implementation of the reform in 2009. In this specification, the set of controls is the same as in Equation 1. However, the coefficient β now captures the average effect of the reform over all the years after the policy change was introduced.

In all the previous specifications, the identification comes from the fact that both the skill of a specialist and the timing of the reform are assumed to be uncorrelated with the shock (ϵ_{ikt}), after controlling for characteristics of the specialists, and the specialist and time-by-specialty fixed effects. In other words, identification relies on the assumption that no unobserved factors are correlated in time with the reform and differentially affect the wages and/or hours worked by specialists of different relative skills (as measured by test scores). Note that the characteristics of the individuals that are fixed over time are captured by the individual fixed effects, while everything that affects the specialties over time, such as technological changes in the specialty or changes in the priorities across specialties in the health care system, is captured by the specialty-by-time fixed effects.

However, a potential concern in these specifications is that, as discussed in the data section, some specialists work at more than one provider, and the previous specification aggregates all hours and wages of specialists at the individual level. To address this concern, another possibility is to define the observations at the individual-by-provider level, having a specialist working in two providers at the same time as two observations. In addition to the previous controls, this specification allows us to control also for all the things that are changing for the same provider over time. Formally, the equation to be estimated is:

$$\text{Log(y)}_{ihkt} \quad = \quad \tilde{\alpha}_{ik} + \tilde{\tau}_{kt} + \mu_{ht} + \beta \begin{bmatrix} \text{Score} \\ \text{Variable} \end{bmatrix}_{ik} \times \begin{bmatrix} \text{Reform} \\ \text{Intensity} \end{bmatrix}_{t} + X_{ikt}\theta + \epsilon_{ihkt} \tag{2}$$

where all the variables and subindices represent the same as before, and now we incorporate the subindex h to represent each provider at which specialists work. Additionally, μ_{ht} represents a provider-by-time fixed effect that captures all the factors that are common for the same provider at each period of time. Note that specialty-by-time fixed effects are also included. In this specification, the coefficient β is estimated only with variation after controlling by individual fixed effects, time variant shocks that happen at the specialty level, and time variant shocks that happen at the provider level. The remaining concerns about endogeneity come from the potential presence of some time variant shocks that happen at the provider-specialty level. However, as was discussed in Section 2, providers in Uruguay are not specialized and consumers receive all medical attention from the same provider, so there are no incentives to develop some specialties over others as a way to compete for consumers.

Finally, it is also possible to test heterogeneous effects across different specialties. This specification is relevant for two reasons: (a) different specialties could have different substitutability between labor and capital, and (b) different specialties could have different bargaining powers through their professional associations. To address this heterogeneity, I estimate a specification where I allow the treatment effect to vary by specialty.

As discussed above, the identification strategy leverages the exogenous change in competition induced by the change in the regulated mobility regime and the fact that the scores are obtained before entering the labor market and therefore exogenous to any endogenous factors, conditional on individual characteristics and a rich set of fixed effects by individual and by specialty-by-time.

6 Results

Table 3 presents the estimates of Equation 1 for the sample of 1,197 specialists. In this sample, each observation of the outcome variable is the average wage per hour (or the total number of hours per month) that the specialist received (worked) in a particular quarter. Therefore, the information for specialists who worked at more than one provider during a period is aggregated across the different providers. Columns I to III present the estimates using log wage as the dependent variable, while Columns IV to VI present the estimates using log hours as the dependent variable. In all panels and columns, standard errors (in parentheses) are clustered at the specialty level.

In Panel A, I use the log score as a measure of skills. Columns I and II present estimates with individual and time fixed effects, and they differ in the inclusion of age controls. Column III is the preferred specification, where age controls as well as individual and time-by-specialty fixed effects are included. This last specification allows control of factors that can change differently over time for different specialties. All the estimates show a positive and significant effect of the intensified competition on returns to skill. To understand the magnitude of these effects, note that the percentage of consumers able to switch rose from 0% to about 60% because of the reform. Therefore, the change in the regulated mobility regime that intensified competition caused an increase of about 1.1 units ($1.8691 \times 0.6 = 1.1215$) in the score elasticity of wages. Therefore, compared to the situation before the reform, after the reform an increase of 1% in the score increased the relative wage by an extra 1.1%. Columns IV to VI follow an analogous presentation, with the first two columns using individual and time fixed effects and the last column using individual and specialty-by-time fixed effects. The effects on hours are generally not statistically significantly different from zero. In the preferred specification, the intensified competition caused an increase of about 0.45 units ($0.7504 \times 0.6 = 0.4502$) in the score elasticity of hours, significant at a 10% level.

In Panel B, the score is used as a measure of skill, instead of the log score. In this specification, we can estimate the effect of one additional point in the score on the increase of returns to skills or relative hours. Again, note that the percentage of consumers able to switch rose from 0% to about 60% because of the reform. Therefore, according to my preferred specifications (Columns III and VI for wages and hours, respectively), compared to the situation before the reform, after the reform an increase of one score point generates a relatively large effect of 3.8 percentage points in wages ($0.0634 \times 0.6 = 0.0380$, significant at a 1% level), while it generates an increase in relative hours of 1.8 percentage points ($0.0301 \times 0.6 = 0.0181$, significant at a 10% level). Since the standard deviation of the scores is 7.09 points, these estimated effects imply that after the reform, a difference of one standard deviation in scores is associated with a wage premium 27 percentage points higher ($0.0380 \times 7.09 = 0.2694$) and a difference in hours worked that is 13 percentage points higher ($0.0181 \times 7.09 = 0.1283$).

Let us now analyze an event study of the effect of the log-score variable by year, by interacting the log score variable with year dummies. I present the results for the estimates of the effect by year, in specifications using a full set of controls, in Figure 3. The top graph in Figure 3 shows the timing of the effects on returns to skills. First, the increase in relative wages coincides with the increase in the intensity of competition (measured as the percentage of beneficiaries able to switch, see Panel A in Figure 1). The largest effects appear around 2011 and 2012, when more people were able to switch providers. In addition, this analysis suggests that the effect on wages is a short-run effect. While the estimated effect has its peak around 2012, it decreases in following two years, and it is not statistically significant in 2014. This reversion to zero in the medium run is expected because of at least two factors. On one hand, the intensity of the reform is lower in the last two years because the number of people able to switch shows some decline at the end of the period. On the other hand, as discussed in Section 3, it is expected that in the long run, as more physicians can enter specialties, the relative supply of high-skill specialists is more elastic, reducing the effect of the demand shock on wages. The bottom graph in Figure 3 shows the size and the timing of the effects on relative hours. The results show that the estimated yearly effects of intensified competition on hours are not statistically significant.

Additionally, I present an alternative way to approximate the effects of the reform by interacting the log score (or the score) with a dummy indicating the period after the reform of 2009. Table A.4 in online Appendix A presents these results for the preferred specification (with individual and specialty-by-time fixed effects, among other controls) in the sample at the individual level. The results in terms of wages and hours are qualitatively similar to the main results.[15]

[15] Regarding relative wages, after the reform there is an increase of 0.7 units in the score elasticity of wages and an increase of almost an additional 2.6 percentage points of wages for each additional point in the score. Regarding hours, the results do

Finally, as discussed in section 3, it is possible that the relative supply of specialists in the short run may be backward bending, that is, that an increase in returns to skill would lead to a reduction in the relative supply of hours, at least for some individuals. Although the main results suggest that wages increase and there is, if any, a small positive effect on hours worked, this could be the result of heterogeneous behavior by individuals, with some increasing their hours worked and others decreasing their hours (backward bending supply). I investigate this possibility by estimating the effect of the reform for individuals who worked different number of hours before the reform.[16] Income and substitution effects should vary across different income levels, so analyzing the effect for different number of hours worked before the reform, directly related to total earnings, is a way to capture these potential effects.

Table 4 shows the results of this exercise. Columns I and II present the results for log wages per hour and log hours, respectively, for four groups of individuals according to the number of hours they worked before the reform: less than 100 hours, between 100 and 200, between 200 and 300 and more than 300 hours. Log wages increase for the four groups, with a slightly larger point estimate for the group that worked more before the reform. The effects on log hours are positive but not statistically significantly different from zero for all groups, with point estimates that decrease and are close to zero as hours worked pre-reform increase. These results suggest that higher income individuals are less prone to increasing their hours worked and have higher returns to skill. However, none of these results are statistically different across groups. Columns III and IV use an alternative specification including the main variable and its interaction with hours worked before the reform. The results show that the effect on wages increases and the effect on hours decreases slightly (but statistically significantly) with hours worked before the reform. However, the point estimate of the effect on wages is always possible and the point estimate of the effect on hours is never negative at in-sample numbers of hours worked. Although the confidence intervals of the effects on hours do not rule out negative effects, the evidence does not support the hypothesis of some individuals having a backward bending supply curve.

Overall, the evidence points to a positive and strong effect of increased competition on returns to skill, and a less clear (if any) effect on relative hours worked. In the case of wages, the event study and the regressions point to a very similar effect and suggest that the effect fades out over time. Regarding

not reject the null hypothesis of no effect of log scores or scores on hours after the reform. The point estimates suggest that the reform generated an increase of 0.07 units in the score elasticity of hours and an additional 0.26 percentage point increase of hours per test score point. These results suggest again a relatively large effect on wages and a small (if any) effect on hours. The fact that the estimates are smaller than the results when we introduce the intensity of the reform is consistent with the timing of the reform, whose effects are larger around 2011 and fade out in the last years after the reform, when the supply of specialists could begin to respond.

[16] In the cases of individuals who enter the sample after the reform, I use their initial total amount of hours worked. The results are robust to including only specialists working before the reform.

hours worked, the event study and the pre- and post-specifications do not reject the hypothesis of a null effect of intensified competition on hours, although the parametric regression analysis shows a significant (but smaller than for wages) effect. In this sense, the evidence in this subsection is consistent with the existence of a relatively inelastic relative supply, where at least most of the effect of the increased competition leads to increases in returns to skills, with only weak evidence of increases in quality (relative hours worked by high-skill specialists). The analyses with interactions with hours worked before the reform provide no evidence of a backward bending labor supply curve, but suggest that specialists working more hours (and earning more) before the reform, have weaker responses in terms of hours of work and higher increases in returns to skills. In the next subsection, I present robustness checks to discuss these results.

6.1 Robustness Checks

One of the main concerns with the previous specifications is the possibility that changes at the provider level over time may affect the wages and hours of the specialists working at each provider. For example, the reform may cause changes in market shares, the competitive positioning of providers or the technology they use, which may differentially affect the earnings and hours worked by all specialists working at the same provider. This would be a concern for my identification strategy if high-skill specialists were distributed differentially across different providers. However, the introduction of provider-by-time fixed effects would allow me to control for these potentially confounding effects. The specifications so far have used data aggregated at the specialist level across the different institutions where specialists worked in each period, so it was not possible to use provider-by-time fixed effects. I construct a new database where the observation is at the level of specialist-by-provider for each period of time. Therefore, if a specialist works at two providers in a particular period of time, this database includes two observations, one per provider. Organizing the database in this way still allows me to control for the specialist fixed effect, the characteristics of the specialists (age and age squared) and the specialty-by-time fixed effects. In addition, in this database it is possible to also control for provider-by-time fixed effects, absorbing all the factors that happen at the provider level in different periods of time.

The results of this exercise are presented in Table 5. The organization of the table in panels and controls by columns is analogous to that of the previous tables, with the difference that all columns include provider-by-time fixed effects. The estimated effects of increased competition on relative wages in this new sample are almost the same as with the sample at the individual level. The estimates of the preferred specification imply that the increased competition increases the elasticity of wages to scores by about 1 unit ($1.7258 \times 0.6 = 1.0355$), and that after the reform, a difference of one point in the test score is associated with an additional increase of 3.4 percentage points in wages ($0.0548 \times 0.6 = 0.0329$). On the other hand, the effects on hours are not statistically significant in any of these specifications. In my preferred specification, the effect of the increased competition on the elasticity of log hours is 0.1 ($0.2037 \times 0.6 = 0.1222$) and it is not statistically significant. The estimated effect of test scores in levels is very close and not statistically different from zero; after the reform, the effect of one additional score point is an increase in hours of about 0.6 percentage points ($0.0102 \times 0.6 = 0.0061$). The results in this robustness check are similar to those found before, with a large effect on wages and a small and non-statistically significant effect on hours, which is consistent with a very inelastic relative supply of high-skill specialists in the short run.

A second potential threat to identification would be any confounding effects of the increased demand caused by the FONASA expansion that differentially affected high- and low-skill workers. To be an identification concern, the increase in demand would need to have two characteristics. First, the timing of the increased demand caused by the FONASA expansion must coincide with the timing of the increased competition. Second, the expansion of FONASA would have to increase the demand for high-skill specialists, for example because of the characteristics of the population obtaining coverage or other factors. It is important to note that if the shock of the FONASA expansion increases the demand proportionally for both high-skill and low-skill specialists, the effects would be captured by the structure of provider-by-time and specialty-by-time fixed effects. If anything, we would expect the expansion of FONASA to increase relatively more the demand for low-skill specialists. FONASA expanded over time from a program that covered formal workers to cover groups that have lower incomes and are therefore likely to have a relatively lower willingness to pay for quality. Additionally, Table 1 shows that the main increase in FONASA consumers took place in 2008, while the increase in competition peaked in 2011 and 2012. However, this concern still requires a more formal approach to check for robustness.

Using the information on the number of FONASA beneficiaries and number of non-FONASA ASSE consumers, it is possible to formally test the robustness of the effects of increased competition to the expansion of FONASA. The idea of the robustness check is to include in the regression an interaction between the score and a variable that represents the size of the FONASA expansion, and to check whether the estimated effect of the increased competition changes in the presence of this new control. I implement two versions of the test using two variables that represent the expansion of FONASA. The first one is the number of beneficiaries covered by FONASA. While representing the increase in FONASA beneficiaries, the shortcoming of this variable is that many consumers who entered FONASA were already (privately) enrolled with one of the providers. In this sense, although this is a first proxy for the demand increase, not all the new FONASA beneficiaries represent a demand pressure for the private providers. Another way to approximate the demand shock is to use the number of non-FONASA consumers in ASSE. Most of the consumers who left the non-FONASA part of ASSE enrolled with private providers. Therefore, a reduction of non-FONASA consumers in ASSE represents an increase in the demand for private providers. Additionally, the individuals who were previously in ASSE are more homogeneous in demographics, so the reduction in the non-FONASA ASSE consumers is likely a better measure of the characteristics of the demand pressure for providers.

The results of these tests are presented in Table 6. Panel A presents the effect of the log scores; Panel B presents the effect of the scores. Columns I and II present the effects when the number of FONASA beneficiaries (in 10,000s) interacted with the score variable is added to my preferred specification for wages and hours, respectively. The estimated effects of increased competition on relative wages in both panels are almost the same in magnitude and statistically significance as in the main specifications. The estimated effects on hours are also qualitatively similar as before in the sense that there are no robust effects on the relative hours worked by high-skill specialists. However, now the point estimates of the effect of increased competition on relative hours is negative (only significant at 10% level), and the effect of the number of FONASA beneficiaries interacted with the score is also negative but not statistically different from zero. Columns III and IV present the effects in the specification that includes the number of non-FONASA ASSE consumers (in 10,000s) interacted with the score variable. Again, the effects of increased competition on skill premiums in both panels are almost the same in magnitude as before. Note that the statistical significance in these specifications is affected due to an increase in the standard errors because we are using the cross-sectional variation in the scores to estimate two separate time effects (increased competition and expansion of FONASA). Regarding hours, once again the effects are qualitatively similar to those of the previous specification, with no robust effects on hours.

Finally, the results are also robust to alternative definitions of the effect of the reform. Currently, I use the ratio of the number of people able to change providers in FONASA over the total number of FONASA beneficiaries. This measure captures the shock of people able to switch after the reform, and therefore the change in competition induced by it. However, people that are not in FONASA can switch at any time, so they are, and were before the reform, also a segment of competition in the system. To account for the total number people who could potential switch providers, it is possible to redefine the main variable of interest as the ratio between the number of people able to change providers in FONASA plus the number of people not in FONASA, divided by the number of people in FONASA plus the number of people not in FONASA. I re-estimate Equation 1 using this alternative measure of competition and present the results in Table A.5 in online Appendix A. The results show that the effects are robust in sign and statistical significance to this alternative measure of competition. Additionally, the magnitude of the estimated effects are very similar and not statistically significantly different to the main estimates. This alternative competition variable changes from about 27 percent in 2008 to 61 percent in 2014. Computing the effect considering that the total change (34 percentage points) is about half of the change we observed in the other competition variable (60 percentage points), leads to very similar estimated effects.

Overall, the results of these robustness tests show that the effect of increased competition on returns to skill is robust to controlling for the expansion of FONASA in several ways. Regarding hours, these robustness tests show that there is no effect on relative hours by skill level.

6.2 Heterogeneity

Age and gender. First, I analyze heterogeneity regarding age and gender. Table 7 presents the results of this analysis. Columns I and II show that the effects on (log) wages and (log) hours, respectively, are not significantly different by gender. Although women seem to have a smaller effect on wages and larger response on hours, these effects are very small and not statistically significant. There is a statistically significant differential effect by age, with the effect on returns to skill increasing with age. Recall that in the sample we have individuals that took the exam from 1996 to 2010, so the sample corresponds to the younger cohorts. This heterogeneity by age suggests that the effect on returns to skill for people that are not in the sample would be larger. The variable age is centered at 35, which is the average age in the sample, so the results reported in column III indicate that effect of the reform on returns to skill for the average age in the sample is 1.06 ($0.60 \times 1.7705 = 1.0596$). The average age for the population of specialists is 46.5, which implies that the predicted average effect of the score elasticity for the population of specialists would be somewhat larger ($0.60 \times (1.77 + (46.5 - 35) \times 0.0263) = 1.2435$) than the average effect for specialists in the sample. On the other hand, Column IV of the same table shows that the effect on relative hours does not change with age, with an estimated coefficient that is very small and not statistically significant.

Exclusive employment. Analyzing the data at the individual-by-provider level allows me to check whether there are heterogeneous effects of intensified competition for specialists who work at only one provider at a time during the sample period. If the mechanism of increased competition is at work, we would expect larger effects for those specialists who have exclusive employment with one provider. Table 8 presents the results for the 826 specialist who work at only one provider during each period. Again, the organization of the table in panels and controls by columns is analogous to that of previous tables. Note that here, and in addition to specialist characteristics, we can control for specialist fixed effects, specialty-by-time fixed effects and provider-by-time fixed effects. Consistent with what we expected, the size of the point estimates for this group of specialists is larger than the size of the previous estimates in terms of returns to skill, although the differences are not statistically significant. For this group, increased competition increases the elasticity of wages to scores by about 1.7 units ($2.9051 \times 0.6 = 1.7431$). A difference of one point in the test score is associated with a large additional effect of 6 percentage points in wages ($0.1010 \times 0.6 = 0.0606$) after the reform.

The effects on hours are also not robust in this sample, with a magnitude of 0.43 units for the elasticity of hours relative to scores ($0.5703 \times 0.6 = 0.34$, significant at a 10% level). A one-point increase in the score generates an additional effect of 1.7 percentage points on hours ($0.0275 \times 0.6 = 0.0165$), not statistically different from zero. These estimated effects imply that after the reform, a one standard deviation difference in scores is associated with a wage premium 44 percentage points higher and an hours-worked difference 12 percentage points higher. These results are consistent with the idea that specialists who behave as if they have exclusive employment at one provider receive a higher return to skill on their wages. At the same time, they are more flexible in terms of work hours after the reform. The latter result is also consistent with the fact that these specialists work fewer hours on average (120.5 hours per month) than the specialists who work at more than one provider (129.5 hours per month).

Among the specialists who worked in only one provider, some switched providers and others worked all the time for the same provider. This is an endogenous decision. Assuming that the wage offers received by specialists who switch and do not switch are similar, making the marginal specialist indifferent between changing providers or not, we would expect the effects of competition to be very similar for these two groups of people. Table A.6 in online Appendix A presents the results for the sample of specialists (717) who worked at the same provider during the whole period. The results on wages and hours under different specifications and controls are very similar to those for the full sample of specialists who worked at only one provider at a time. The point estimates for wages are almost identical while the point estimates for hours are slightly larger, but not statistically different from the results for all the specialists who worked at one provider a time. Overall, conditional on working at one provider at a time, this evidence suggests that no differences exist between the effects for those specialists who change providers or those who remain employed at the same provider the whole time, showing the expected equalization among job offers. However, it should be noted that the sample of specialists who work at one provider at a time but have switched jobs is quite small, so even if there were any differences between these two groups, I have very little power to identify them.

Specialties. The effects of the reform may be heterogeneous across specialties, in terms of both wages and hours. As discussed before, we can expect these differences for at least two reasons. On one hand, different specialties may have different demand shocks, and therefore demand shocks may affect them differently. One possible reason for this difference is that specialties have varying degrees of substitutability between capital and labor. Another reason could be that the reform puts more pressure on the demand for certain specialties, such as those related to primary care. On the other hand, different specialties may have different levels of barriers to entry, for example due to different quotas in each specialty's graduate studies. Therefore, this scarcity and lag in (or lack of) response on the supply side could be expressed in larger effects on wages of the demand increase.

One way to approximate the heterogeneity of effects across specialties is to run our regressions separately by specialty and to compare the size of the estimated effects. The results of this exercise are presented in Table 9. First, the larger increases of returns to skill are associated with specialties with more scarcity, in which there are higher barriers to entry. For example, anesthesiology has one of the largest estimated effects on wages (5.6 units in the elasticity), and it is a specialty for which all the anecdotal evidence and the news point to large barriers to entry. Second, large effects on returns to skill are present in some specialties that are likely to have received a stronger demand pressure after the reform. One example is an area related to primary care, such as pediatrics, which has an increase in the score elasticity of wages of 2.5 units. However, one limitation of this analysis is that the sample is reduced when it is split by specialty, and therefore some of these estimations are done with small samples.

Markets. Finally, since the level of baseline competition can vary by market, it is interesting to check if the effects on skill premiums and hours are different in the capital city, Montevideo. This city offers a particularly good setting to understand the effects of competition, since over half of the country's population lives in its metropolitan area and it has the largest number of providers (11) competing for FONASA consumers. In this sense, the competitive pressure for quality should be even clearer in this setting than in the full sample of specialists. I run the analysis for the sample that includes only hours and wages that specialists received (worked) in Montevideo in a particular quarter. There are 987 specialists working at providers in Montevideo, which represents 75% of the total number of specialists. This large percentage can be explained by the fact that many specialists work most of their hours in Montevideo but also work some hours at providers outside the capital city, typically one day a week.

Figure A.3 in online Appendix A presents the event-study for wages (first three columns) and hours (last three columns). The results for Montevideo are qualitatively similar to the results when all the markets are included: increased competition increases the score elasticity of wages, but it does not have significant effects on hours worked. Additionally, the timing of the effect is similar. The results of the event-study are confirmed with the regression analysis for Montevideo, presented in Table A.7 in online Appendix A. Consistent with the idea of higher competition in this market, the effects on wages are larger. For an increase in the percentage of consumers able to switch from 0% to 60%, the estimates imply an increase of 1.68 units in the score elasticity of wages and of 5.9 percentage points in relative wages per extra score point (42 percentage points for a difference of one standard deviation in scores). On the other hand, in Montevideo it is not possible to reject the null hypothesis that the reform did not increase the hours of the relatively high skilled, and therefore did not increase the total quality of the health care system. The results of the specification using a dummy for post-reform interacted with the scores (available upon request) are consistent with these results.

7 Conclusions

In health care markets, increases in competition, such as those generated by reductions of inertia, may lead to greater incentives for firms to compete in quality. Following these incentives, providers may increase the demand for high-skill physicians. The effects of a higher demand for high-skill physicians depend on the elasticity of the relative supply of higher- and lower-skill physicians. If the relative supply is inelastic, an increase in the demand for high-quality physicians will lead to an increase in their relative wages (skill premium) without increasing their total hours of work, and thus without changing the average quality of the health care system, but increasing its costs.

In this paper, I assess these predictions using a quasi-experimental setting in the Uruguayan health care system. I leverage a change in the regulated mobility scheme as a shock that increases the competition in the market, to estimate the effects on returns to skill and relative hours of work for specialists with different levels of skills. I use information on scores in the admissions test for medical specialty graduate school as an exogenous measure of the quality of specialists. To the best of my knowledge, this paper is the first to use test scores of physicians in a systematic way to understand the effects of competition shocks on returns to skill.

The results of this paper are consistent with the hypothesis of increased competition generating incentives to increase quality, together with a relatively inelastic supply of high-skill specialists. Intensified competition caused a relatively large increase in the returns to skill of specialists. However, I do not find robust evidence of an increase in the relative hours worked by high-skill compared to low-skill specialists. In this sense, the reform generated only small (if any) increases in the total quality of the system, measured as the amount of hours weighted by the skill of the specialists.

Overall, the results show that, in a context of inelastic labor supply, the potential benefits of increased competition in terms of quality can be absorbed by increases in wages. In particular, it underscores the differences between the strategies of adopting more capital, with a relatively more elastic supply, and the adoption of human capital, which in the short run has a very inelastic supply in professions that require licenses. These results highlight how the flexibility of the input markets mediates the effects of competition in the output market both in terms of quality and reallocation effects. Future work should analyze the implications on consumer welfare of these changes in competition, quality, and reallocation across providers.

From a policy point of view, this paper sheds light on the importance of paying attention to labor markets when the product market that demands these human resources has an increase in competition or receives a demand shock in sectors with regulations or licenses. In particular, it underscores the importance of understanding the labor markets of physicians and their regulations, and especially the quotas for entrance to graduate school and the role of professional associations. This attention to labor markets is crucial for understanding how the markets for human resources work in the health care sector, and how costs may increase and the distribution of rents change with the implementation of a public policy that generates demand shocks for physicians.

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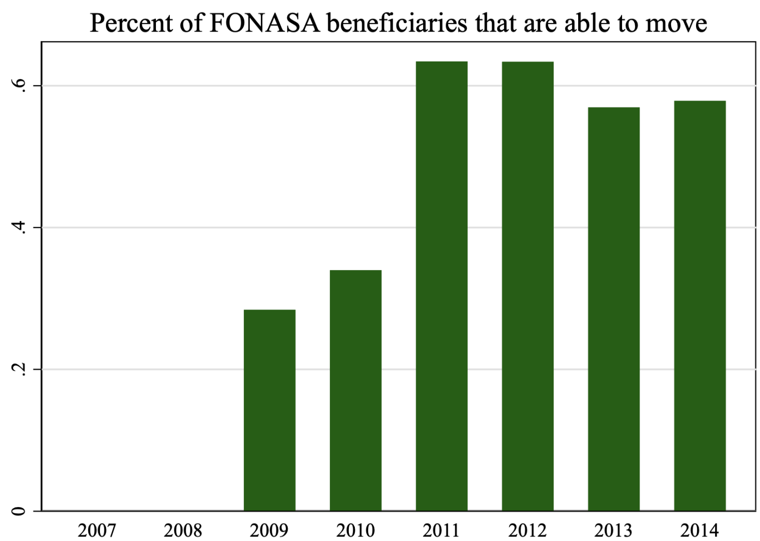
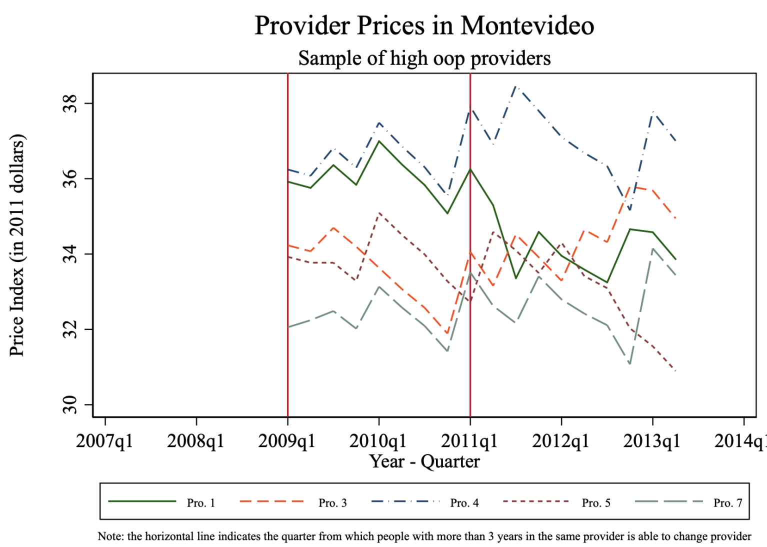
Figure 1: Regulated mobility and increased competition

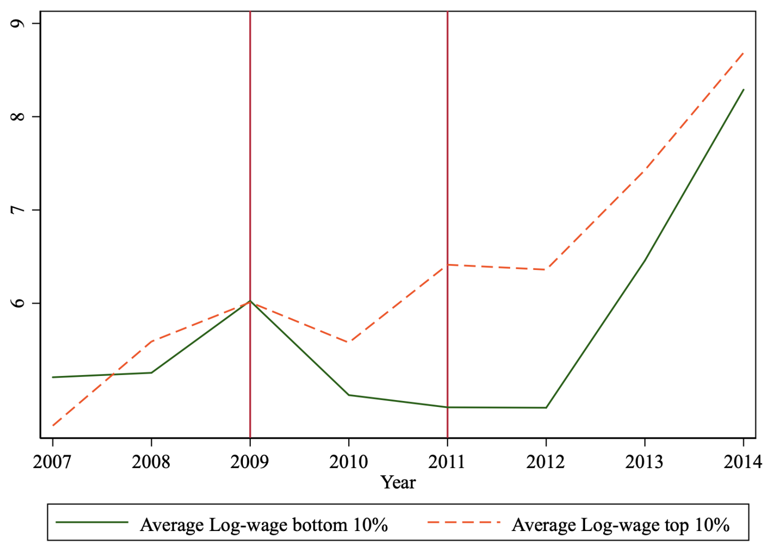


(a) FONASA consumers able to switch providers

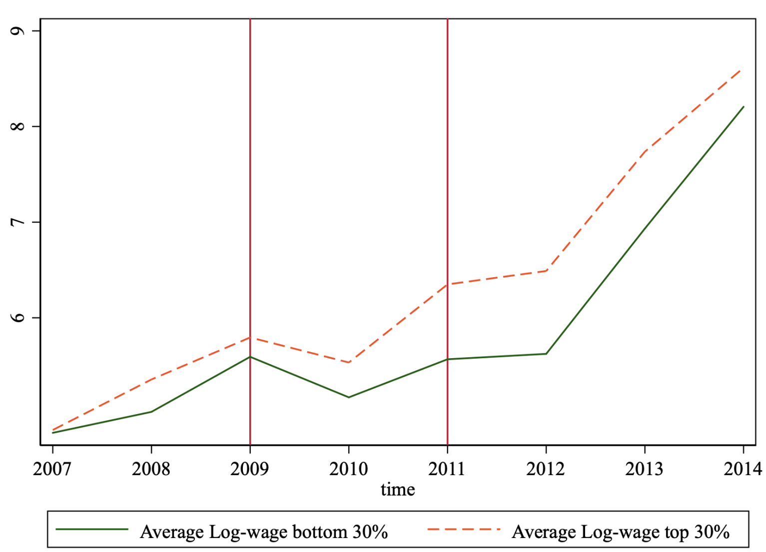


(b) Out-of-pocket prices and increased competition

Figure 2: Evolution of log-wage for different levels of skills

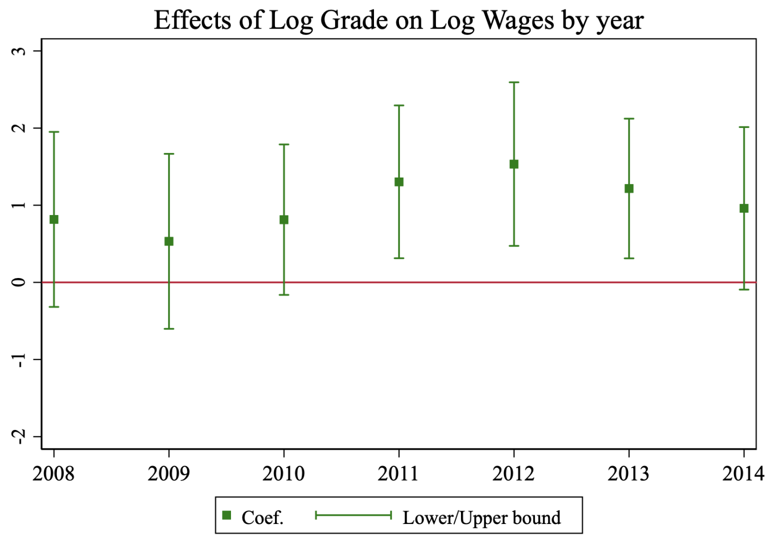


(a) Log-wage difference between top and bottom 10 percent

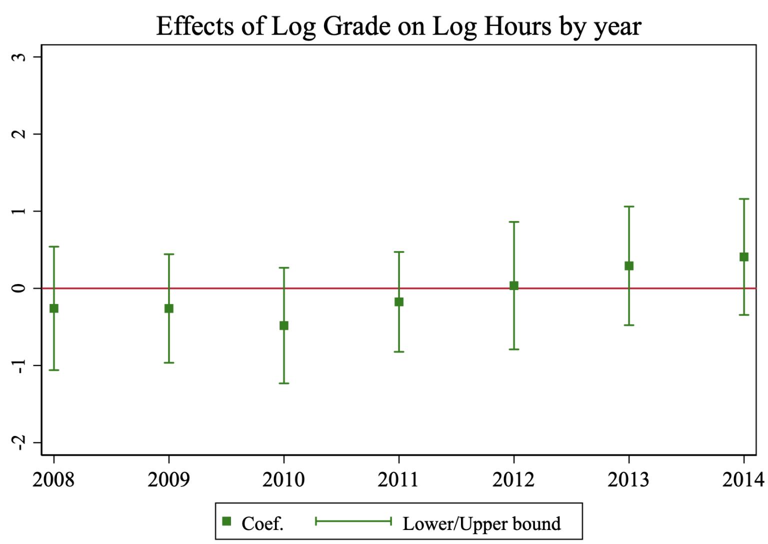


(b) Log-wage difference between top and bottom 30 percent

Figure 3: Even Study: All Markets



(a) Effects of Score on Log Wages by year



(b) Effects of Score on Log Hours by year

For all markets in the sample, these graphs show the point estimates from regressions with different effects by year, and the shaded area illustrates 95% (light gray) confidence intervals.

Table 1: Number of consumers able to change and changes

	2007	2008	2009	2010	2011	2012	2013	2014
Uruguayan population	3,358,793	3,363,059	3,378,082	3,396,705	3,412,636	3,426,466	3,440,157	3,453,690
Non-FONASA ASSE consumers	1,282,880	1,114,190	1,113,157	1,073,656	990,805	928,552	906,716	879,102
People covered by FONASA	754,484	1,412,319	1,493,051	1,555,826	1,827,881	2,108,736	2,251,362	2,333,833
FONASA beneficiaries able to switch	0	0	424,069	528,850	1,159,387	1,336,444	1,281,970	1,350,473
% FONASA able to switch	0%	0%	28.40 %	33.99 %	63.42 %	63.38 %	56.94 %	57.86 %
Stayers			341,317	417,027	1,000,084	1,204,059	1,205,492	1,272,010
Switchers			82,752	111,823	159,303	132,385	76,478	78,462
% Switchers			19.51 %	21.14 %	13.74 %	9.90 %	5.96 %	5.81 %

Note: This table presents the descriptive statistics (population in Uruguay, non-FONASA ASSE consumers, total number of FONASA beneficiaries, number of FONASA beneficiaries allowed to switch providers, number who switch and number who stay enrolled with the same provider) for the regulated mobility system in Uruguay.

Table 2: Descriptive Statistics for total number of specialists and sample

	All Specialists			Sample		
	All	One Provider Per Period	Several Providers Per Period	All	One Provider Per Period	Several Providers Per Period
Female	0.62	0.62	0.61	0.70	0.72	0.66
	(0.48)	(0.48)	(0.48)	(0.45)	(0.45)	(0.46)
Age	46.51	45.55	48.29	35.22	34.71	36.21
	(10.89)	(11.47)	(9.50)	(4.57)	(4.58)	(4.39)
Wage per Hour	29.03	30.4	26.49	16.43	15.89	17.5
	(135.17)	(152.79)	(94.52)	(33.77)	(39.27)	(18.66)
Hours	166.07	174.02	151.46	123.54	120.50	129.53
	(191.44)	(206.78)	(158.44)	(122.25)	(121.49)	(123.66)
Score				27.37	26.73	28.61
				(7.09)	(7.38)	(6.31)
N Specialists	5401	3498	1903	1197	826	371
%		64.77	35.23		69.01	30.99

Notes: This table presents the descriptive statistics for the full data and for the sample. The sample includes all specialists for whom the information about the test scores is available. Female is a dummy variable that takes the value of 1 if gender is female. Wage per hour is measured in constant (2011) US dollars. Score is the grade obtained in the exam to enter into graduate studies (which ranges from 10 to 40). Each of these samples is in turn split between those who worked at only one provider at a time and those who worked in more than one provider at a time.

Table 3: Effects of lock-in reduction on returns to skill and relative hours at individual level

	I	II	III	IV	V	VI
	Panel A: Effects of Log Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Log(Score$_{ik}$) $\times$	2.1739***	2.2029***	1.8691***	0.2242	0.2221	0.7504+
Able to Change$_t$	(0.5249)	(0.5184)	(0.5300)	(0.4154)	(0.4096)	(0.4211)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	12352	12352	12352	12352	12352	12352
Specialists	1197	1197	1197	1197	1197	1197
	Panel B: Effects of Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Score$_{ik}$ $\times$	0.0769***	0.0787***	0.0634***	0.0094	0.0095	0.0301+
Able to Change$_t$	(0.0205)	(0.0203)	(0.0211)	(0.0173)	(0.0171)	(0.0182)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	12352	12352	12352	12352	12352	12352
Specialists	1197	1197	1197	1197	1197	1197

This table presents the estimates of Equation 1. Each observation in the sample is the aggregate average wage (total hours) that a specialist received (worked) in a particular quarter. Columns I to III present the estimates using Log(Wages) as the dependent variable, while Columns IV to VI present the estimates using Log(Hours) as the dependent variable. In Panel A, the log of the score is used to construct the main variable of interest while in Panel B, the score in levels is used. All estimates are obtained using specialist fixed effects. Age controls (age and age squared) are included in some specifications. Columns I, II, VI and V include time fixed effects at the quarter level. Columns III and VI include time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table 4: Substitution and Income effects by hours worked before the reform

	I	II	III	IV
	Dependent variable:			
	Log(Wages)	Log(Hours)	Log(Wages)	Log(Hours)
Log(Score$_{ik}$) $\times$ Able to Change$_t$	2.0331***	0.5619		
$\times$ Up to 100hs worked before$_i$	(0.5222)	(0.4196)		
Log(Score$_{ik}$) $\times$ Able to Change$_t$	2.1651***	0.2724		
$\times$ 100hs to 200hs worked before$_i$	(0.5317)	(0.4250)		
Log(Score$_{ik}$) $\times$ Able to Change$_t$	2.0691***	0.0884		
$\times$ 200hs to 300hs worked before$_i$	(0.5200)	(0.4070)		
Log(Score$_{ik}$) $\times$ Able to Change$_t$	2.3960***	0.0415		
$\times$ 300+ hs worked before$_i$	(0.5303)	(0.4281)		
Log(Score$_{ik}$) $\times$ Able to Change$_t$			1.9765***	0.5567
			(0.5210)	(0.4146)
Log(Score$_{ik}$) $\times$ Able to Change$_t$			0.0006***	-0.0010***
$\times$ hours worked before$_i$			(0.0002)	(0.0002)
Indiv.FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Time-Spec. FE	Yes	Yes	Yes	Yes
Observations	12352	12352	12352	12352

This table columns presents the estimates of the effect of increased competition on returns to skills and relative hours, interacted with four groups of hours worked before the reform (first two columns) or the number of hours worked before the reform (last two columns). Each observation in the sample is the wage (hours) the specialist received (worked) in a particular quarter. Columns I and III present the estimates using Log(Wages) as the dependent variable, while Columns II and IV present the estimates using Log(Hours) as the dependent variable. Age controls (age and age squared) are included in all specifications. All estimates are obtained using specialist fixed effects and specialty-by-time fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table 5: Effects of lock-in reduction including provider-by-time fixed effects (individual-provider level)

	I	II	III	IV	V	VI
	Panel A: Effects of Log Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Log(Score_{ik}) $\times$	1.9256***	1.9861***	1.7258***	-0.3788	-0.3569	0.2037
Able to Change_t	(0.3933)	(0.4293)	(0.4770)	(0.4670)	(0.4707)	(0.3200)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Provider-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	15450	15450	15450	15450	15450	15450
Specialists	1197	1197	1197	1197	1197	1197
	Panel B: Effects of Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Score_{ik} $\times$	0.0643***	0.0674***	0.0548**	-0.0135	-0.0124	0.0102
Able to Change_t	(0.0178)	(0.0196)	(0.0216)	(0.0188)	(0.0192)	(0.0137)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Provider-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	15450	15450	15450	15450	15450	15450
Specialists	1197	1197	1197	1197	1197	1197

This table presents the estimates of the effect of increased competition on returns to skills and relative hours. Each observation in the sample is the wage (hours) the specialist received (worked) in a particular quarter at a particular provider. Columns I to III present the estimates using Log(Wages) as the dependent variable, while Columns IV to VI present the estimates using Log(Hours) as the dependent variable. In Panel A, the log of the score is used to construct the main variable of interest while in Panel B, the score in levels is used. Age controls (age and age squared) are included in some specifications. All estimates are obtained using specialist fixed effects and provider-by-time fixed effects. Columns III and VI also include time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table 6: Robustness of increases in FONASA coverage

	I	II	III	IV
	Dependent variable:			
	Log(Wages)	Log(Hours)	Log(Wages)	Log(Hours)
	Panel A: Effects of Log Score			
Log(Score$_{ik}$) $\times$	1.8131**	-0.6703	1.7145**	-0.9069+
Able to Change$_t$	(0.7496)	(0.4916)	(0.8096)	(0.5341)
Log(Score$_{ik}$) $\times$	-0.0004	0.0098***		
FONASA beneficiaries$_t$	(0.0038)	(0.0027)		
Log(Score$_{ik}$) $\times$			-0.0038	-0.0411***
Non-FONASA in ASSE$_t$			(0.0160)	(0.0116)
Indiv.FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Time-Spec. FE	Yes	Yes	Yes	Yes
Observations	12352	12352	12352	12352
Specialists	1197	1197	1197	1197
	Panel B: Effects of Score			
Score$_{ik}$ $\times$	0.0581**	-0.0239	0.0541	-0.0322
Able to Change$_t$	(0.0294)	(0.0206)	(0.0314)	(0.0222)
Score$_{ik}$ $\times$	0.0000	0.0004**		
FONASA beneficiaries$_t$	(0.0001)	(0.0001)		
Score$_{ik}$ $\times$			-0.0002	-0.0015***
Non-FONASA in ASSE$_t$			(0.0006)	(0.0005)
Indiv.FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Time-Spec. FE	Yes	Yes	Yes	Yes
Observations	12352	12352	12352	12352
Specialists	1197	1197	1197	1197

This table presents the estimates of the effect of increased competition on returns to skills and relative hours controlling for the expansion of FONASA. Each observation in the sample is the aggregate average wage (total hours) that a specialist received (worked) in a particular quarter. Panel A presents the effects when the log score is used; Panel B, when the score in levels is used. Columns I to II present the estimates for log(wages) and log(hours) when controlling also for the number of beneficiaries in FONASA (in 10,000s). Columns III and IV present the estimates for log(wages) and log(hours) when controlling also for the number of non-FONASA consumers in the public provider, ASSE (in 10,000s). All columns include individual fixed effects, age controls (age and age squared) and time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table 7: Heterogeneity of effects by age and gender on (log) wages and hours

	I	II	III	IV
	Dependent variable:			
	Log(Wages)	Log(Hours)	Log(Wages)	Log(Hours)
$\text{Log(Score}_{ik}) \times$	1.9619***	0.6908	1.7705***	0.7355+
Able to Change_t	(0.5397)	(0.4203)	(0.5233)	(0.4208)
$\text{Log(Score}_{ik}) \times$	-0.0916	0.0588		
$\text{Able to Change}_t \times \text{Female}_i$	(0.0856)	(0.0685)		
$\text{Log(Score}_{ik}) \times$			0.0263***	0.0040
$\text{Able to Change}_t \times \text{Age}_i$			(0.0096)	(0.0068)
Indiv.FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Time-Spec. FE	Yes	Yes	Yes	Yes
Observations	12352	12352	12352	12352

This table presents the estimates of the effect of increased competition on returns to skills and relative hours, as well as its interaction with gender (first two columns) and age (last two columns). Age is centered at the mean age of the sample (35 years old). Each observation in the sample is the wage (hours) the specialist received (worked) in a particular quarter. Columns I and III present the estimates using Log(Wages) as the dependent variable, while Columns II to IV present the estimates using Log(Hours) as the dependent variable. Age controls (age and age squared) are included in all specifications. All estimates are obtained using specialist fixed effects and specialty-by-time fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table 8: Effects of lock-in reduction at individual-provider level (only one provider sample)

	I	II	III	IV	V	VI
	Panel A: Effects of Log Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Log(Score$_{ik}$) $\times$	2.6798***	2.7077***	2.9051***	-0.3248	-0.3206	0.5703+
Able to Change$_t$	(0.4722)	(0.4509)	(0.4679)	(0.5046)	(0.5106)	(0.2960)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Provider-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	6927	6927	6927	6927	6927	6927
Specialists	826	826	826	826	826	826
	Panel B: Effects of Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Score$_{ik}$ $\times$	0.0919***	0.0947***	0.1010***	-0.0118	-0.0114	0.0275
Able to Change$_t$	(0.0213)	(0.0206)	(0.0251)	(0.0219)	(0.0226)	(0.0160)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Provider-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	6927	6927	6927	6927	6927	6927
Specialists	826	826	826	826	826	826

This table presents the estimates of the effect of increased competition on returns to skills and relative hours. Each observation in the sample is the wage (hours) the specialist received (worked) in a particular quarter at a particular provider. The sample includes only specialists who worked at just one provider during each period of time. Columns I to III present the estimates using Log(Wages) as the dependent variable, while Columns IV to VI present the estimates using Log(Hours) as the dependent variable. In Panel A, the log of the score is used to construct the main variable of interest while in Panel B, the score in levels is used. Age controls (age and age squared) are included in some specifications. All estimates are obtained using specialist fixed effects and provider-by-time fixed effects. Columns III and VI also include time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table 9: Heterogeneous effects on (log) wages and hours by specialty

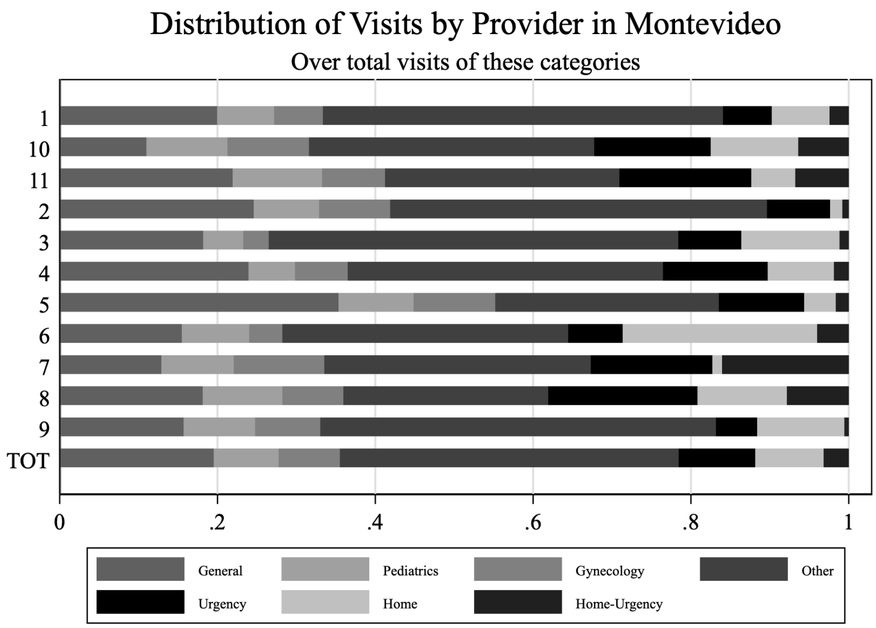
	I	II	III	IV	
	Log(Wages)		Log(Hours)		Obs.
	Coef.	S.E.	Coef.	S.E.	
Anatomic pathology	6.2579*	3.0918	-1.8194	3.918	104
Anesthesiology	13.1609***	3.9808	-2.7202	3.1916	380
Cardiology	2.6755	1.9843	4.6668***	1.9326	597
Surgery	-3.3471	6.2588	-0.4535	1.4454	113
Dermatology	-0.5274	1.8777	-3.8945	2.5028	513
Endocrinology	1.9093	2.0968	3.202*	1.629	263
Infectious Disease	1.9879*	1.0498	2.3467**	0.9442	218
Gynecology	17.1124	16.8507	-9.9534**	4.4892	173
Hematology	1.2470*	0.7164	1.7818**	0.7773	215
Diagnostic Radiology	1.2618	0.9613	0.581	0.8473	2753
Internal Medicine	3.109**	1.4945	1.5038*	0.784	2680
Nephrology	-5.6535	5.2089	4.6186	3.2027	134
Neurology	-2.9089**	1.2814	-1.647	3.1258	104
Oncology	-1.3079	1.511	-0.9664	2.0587	379
Pediatry	4.1057***	1.2506	0.4195	0.7045	1436
Psychiatry	0.6756	1.3621	-0.7867	1.7307	1300

This table presents separate estimates of Equation 1 for each medical specialty. Each observation in the sample is the aggregate average wage (hours) the specialist received (worked) in a particular quarter. Columns I and III present the point estimates of the effect of scores interacted with the percentage of consumers able to switch on Log(Wages) and Log(Hours), respectively. Columns II and VI present the standard errors (clustered at the individual level) for each point estimate. Column V presents the number of observations. All estimates are obtained using specialist fixed effects, age controls (age and age squared) and time-by-specialty fixed effects. +.10 **.05 *** .01.

A Appendix

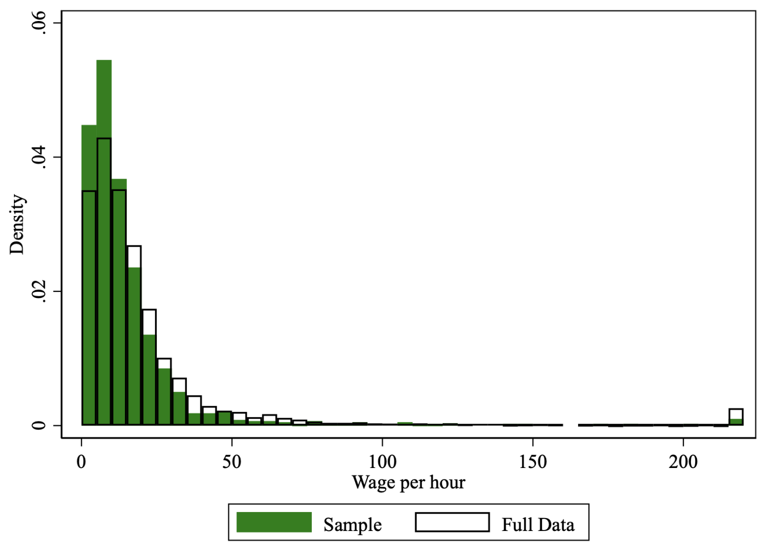
A.1 Online Appendix A

Figure A.1: Specialization and providers

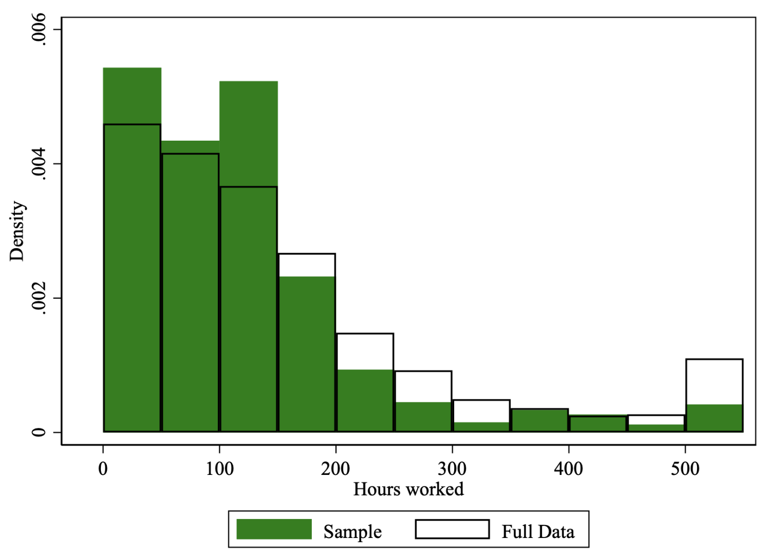


(c) Distribution of visits in Montevideo, Year 2012

Figure A.2: Histograms of full data and sample

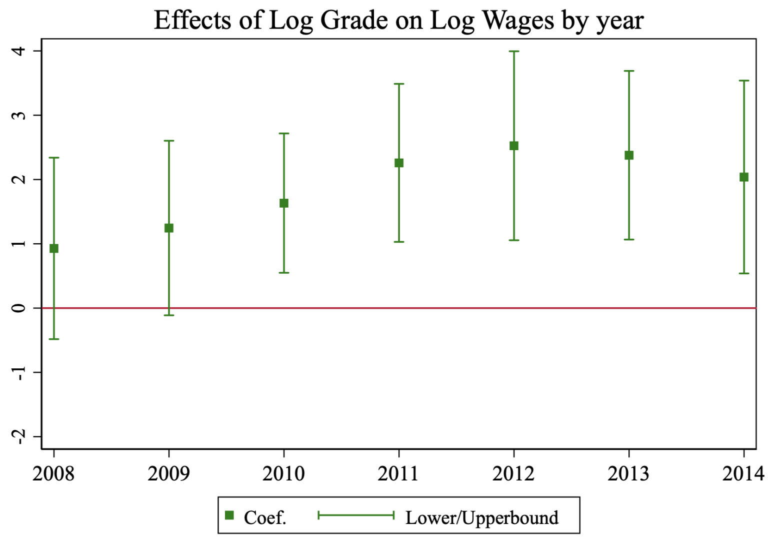


(a) Histogram of wage per hours

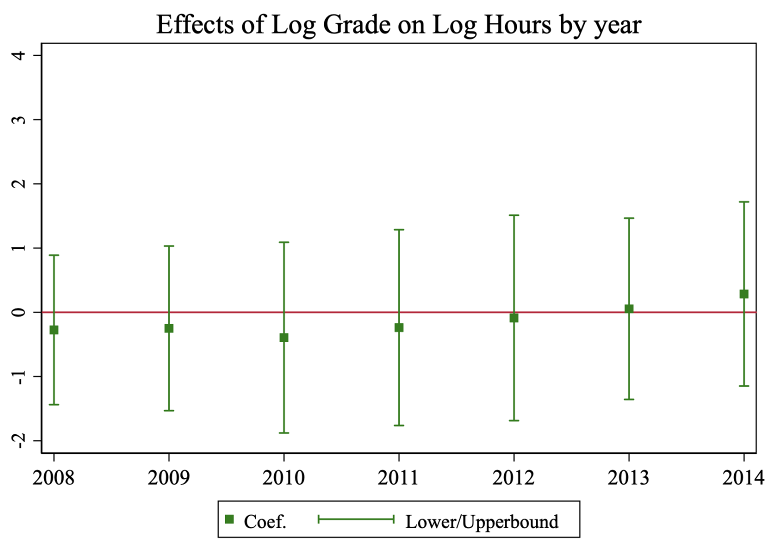


(b) Histogram of hours worked

Figure A.3: Even Study: capital city Montevideo



(a) Effects of Score on Log Wages by year



(b) Effects of Score on Log Hours by year

Note: For the market of the capital city, Montevideo, these graphs show the point estimates from regressions with different effects by year and the shaded area illustrates 95% (light gray) confidence intervals (with clustered standard errors).

Table A.1: Correlation between Scores and Log Wages before the reform

	I	II	III	IV
	Dependent variable: Log(Wages)			
Log Score$_{ik}$	0.5296***	0.6917***		
	(0.1940)	(0.2042)		
Score$_{ik}$			0.0229***	0.0277***
			(0.0072)	(0.0075)
Time FE	Yes	Yes	Yes	Yes
Specialty FE	No	Yes	No	Yes
Observations	986	986	986	986

This table shows estimated coefficients from regressing log wages on log score (columns I and II) or score (columns III and IV). The sample includes all observations from the main sample before the reform. Standard errors (in parenthesis). +.10 **.05 *** .01.

Table A.2: Correlations between quality measure and costs, waiting times and assistential variables

	I	II	III	IV	V
	Panel A: Cost and Waiting Times Variables				
	Cost by Enrollee	Average Waiting Time General	Average Waiting Time for Pediatrics	Average Waiting Time for Gynecology	Average Waiting Time for Cardiology
Log Score$_{ik}$	-0.6988***	-5.4686***	-4.7586***	-3.7249**	-1.5142
	(0.2377)	(1.8207)	(1.5767)	(1.4293)	(1.3296)
Provider FE	Yes	No	No	No	No
N	150	35	35	35	35
	Panel B: Assistential Quality Variables				
	Hospital Readmissions	Ratio of C-sections	% of Early Pregnancy Control	Ratio Non-Urgent to Urgent Admissions	Ratio Inpatients Visits to Urgency Admissions
Log Score$_{ik}$	-1.2313+	-0.5261**	1.4217***	0.0449	0.1741
	(0.7268)	(0.2537)	(0.4076)	(0.2600)	(0.2347)
Provider FE	Yes	Yes	Yes	Yes	Yes
N	74	74	74	74	74

This table presents the correlation between the quality measure by provider (the log of the average score of specialist by provider) and different measures of quality by provider. Column I of Panel A presents the correlation between the quality measure by provider and the average cost of services (which the regulator make available yearly from 2007 to 2011) using provider fixed effects. Columns II to V of Panel A present the correlates between the quality measure by provider and some measures of waiting times (which the regulator has made available once during the period in 2010). Columns I to V in Panel B present the correlation between the quality measure by provider and some assistential variables (which the regulator made available twice during the period in 2007 and 2011) using provider fixed effects. These variables are hospital readmissions, ratio of C-sections, % of early (first trimester) pregnancy control, ratio of urgent to non-urgent hospital admissions and ratio of inpatient visits to urgency hospital readmissions. Standard errors (in parenthesis). +.10 **.05 *** .01.

Table A.3: Correlations between quantity and average quality measure by provider

	I	II	III	IV
	Dependent variable: Log(Enrollees)			
Average($Score_{ik}$)	0.5913***	0.6353***	0.0322**	0.0323**
	(0.0236)	(0.0321)	(0.0140)	(0.0140)
Out-of-Pocket Price		-0.4727***		0.0775
		(0.1445)		(0.1391)
Provider FE	No	No	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	652	652	652	652
Providers	38	38	38	38

This table shows estimated coefficients from regressions of the log of number of enrollees of each provider on the average score of sample specialists working at the provider and an index of out-of-pocket prices. Standard errors (in parenthesis). +.10 **.05 *** .01.

Table A.4: Post-reform effects on returns to skill and relative hours.

	I	II	III	IV
	Dependent Variable: Log(Wages)		Dependent Variable: Log(Hours)	
Log(Score$_{ik}$) $\times$ After Reform	0.6846** (0.3406)		0.0706 (0.3216)	
Score$_{ik}$ $\times$ After Reform		0.0256+ (0.0133)		0.0026 (0.0125)
Indiv.FE	Yes	Yes	Yes	Yes
Age Controls	Yes	Yes	Yes	Yes
Time Espec. FE	Yes	Yes	Yes	Yes
Observations	12352	12352	12352	12352
Specialists	1197	1197	1197	1197

This table presents the estimates of the effect of increased competition on returns to skills and relative hours. Each observation in the sample is the aggregate average wage (hours) the specialist received (worked) in a particular quarter. Columns I and II present the estimates using Log(Wages) as dependent variable while Columns III and IV present the estimates using Log(Hours) as the dependent variable. The main variable in these regressions is the interaction between the log of the score (columns I and III) or the score (columns II and IV) and a dummy that indicates the period after the regulated mobility reform (2009). All columns include individual fixed effects, age controls (age and age squared) and time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table A.5: Effects of alternative competition variable (log) wages and hours

	I	II	III	IV	V	VI
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Log(Score$_{ik}$) $\times$	3.2547***	3.3268***	2.7832***	0.0349	0.0419	0.8224
$\left(\frac{\text{Able to Change + non-FONASA}}{\text{FONASA + non-FONASA}}\right)_t$	(0.8367)	(0.8283)	(0.8567)	(0.5970)	(0.5874)	(0.6170)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	12352	12352	12352	12352	12352	12352

This table presents the estimates of the effect of increased competition on returns to skills and relative hours, using log score interacted with an alternative measure of the competition shock (the number of people able to change providers in FONASA plus the number of people not in FONASA, divided by the number of people in FONASA plus the number of people not in FONASA). Each observation in the sample is the wage (hours) the specialist received (worked) in a particular quarter. Columns I to III present the estimates using Log(Wages) as the dependent variable, while Columns IV to VI present the estimates using Log(Hours) as the dependent variable. All estimates are obtained using specialist fixed effects, age controls (age and age squared) and specialty-by-time fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table A.6: Effects of lock-in reduction at individual-provider level (only same provider sample)

	I	II	III	IV	V	VI
			Panel A: Effects of Log Score			
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
$\text{Log(Score}_{ik}) \times$	2.3972***	2.4412***	2.8851***	-0.2441	-0.2420	0.7167**
Able to Change_t	(0.5618)	(0.5506)	(0.4576)	(0.5347)	(0.5430)	(0.3048)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Provider-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	5969	5969	5969	5969	5969	5969
Specialists	717	717	717	717	717	717
			Panel B: Effects of Score			
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
$\text{Score}_{ik} \times$	0.0807***	0.0845***	0.1035***	-0.0078	-0.0076	0.0344+
Able to Change_t	(0.0247)	(0.0247)	(0.0232)	(0.0233)	(0.0243)	(0.0171)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Provider-by-Time FE	Yes	Yes	Yes	Yes	Yes	Yes
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	5969	5969	5969	5969	5969	5969
Specialists	717	717	717	717	717	717

This table presents the estimates of the effect of increased competition on returns to skills and relative hours. Each observation in the sample is the wage (hours) the specialist received (worked) in a particular quarter at a particular provider. The sample includes only specialists who worked in the same provider during the whole sample period. Columns I to III present the estimates using Log(Wages) as the dependent variable while Columns IV to VI present the estimates using Log(Hours) as the dependent variable. In Panel A, the log of the score is used to construct the main variable of interest while in Panel B, the score in levels is used. Age controls (age and age squared) are included in some specifications. All estimates are obtained using specialist fixed effects and provider-by-time fixed effects. Columns III and VI also include time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.

Table A.7: Effects of lock-in reduction at individual level (Montevideo only)

	I	II	III	IV	V	VI
	Panel A: Effects of Log Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Log(Score$_{ik}$) $\times$	3.2704***	3.2448***	2.7935***	-0.3024	-0.3107	0.4747
Able to Change$_t$	(0.6215)	(0.6158)	(0.6555)	(0.5698)	(0.5378)	(0.5063)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	9417	9417	9417	9417	9417	9417
Specialists	987	987	987	987	987	987
	Panel B: Effects of Score					
	Dependent Variable: Log(Wages)			Dependent Variable: Log(Hours)		
Score$_{ik}$ $\times$	0.1190***	0.1186***	0.0981***	-0.0089	-0.0089	0.0219
Able to Change$_t$	(0.0283)	(0.0278)	(0.0306)	(0.0249)	(0.0237)	(0.0241)
Indiv.FE	Yes	Yes	Yes	Yes	Yes	Yes
Age Controls	No	Yes	Yes	No	Yes	Yes
Time FE	Yes	Yes	No	Yes	Yes	No
Time-Spec. FE	No	No	Yes	No	No	Yes
Observations	9417	9417	9417	9417	9417	9417
Specialists	987	987	987	987	987	987

This table presents the estimates of Equation 1. Each observation in the sample is the aggregate average wage (hours) the specialist received (worked) in a particular quarter. The sample includes only wages and hours that specialists received and worked in providers in the capital city, Montevideo. Columns I to III present the estimates using Log(Wages) as the dependent variable while Columns IV to VI present the estimates using Log(Hours) as the dependent variable. In Panel A, the log of the score is used to construct the main variable of interest while in Panel B, the score in levels is used. All estimates are obtained using specialist fixed effects. Age controls (age and age squared) are included in some specifications. Columns I, II, VI and V include time fixed effects, and Columns III and VI include time-by-specialty fixed effects. Standard errors (in parenthesis) are clustered at the specialty level. +.10 **.05 *** .01.