Lemon Dropping: Do physicians respond to incentives?*

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November 21, 2017

Abstract

I analyze a novel panel dataset on the U.S. primary care physician population, their practice patterns, and their financial incentives. There is geographic variation in practice costs and payment regulations from Medicare and Medicaid. I document several facts regarding physician migration across locations, acceptance of Medicare Part B and Medicaid Dual Eligible patients, and the medical procedures supplied to accepted patients. Motivated by these facts, I exploit physician migration to identify the effects of financial incentives on patient acceptance and practice patterns, and to estimate the migrant's response to broader environmental factors. I find that physicians are more likely to accept more profitable patients. However, environmental factors can only explain 45% of the change in patient acceptance following migration, and only 21-32% of the change in practice patterns. I use a structural supply model to estimate idiosyncratic financial incentives that affect acceptance and practice patterns. I find that the opportunity cost of labor is higher for Medicaid than for Medicare. For Medicare patients, I find that the opportunity costs of malpractice risk and medical equipment are most important. The estimates imply that equalizing Medicaid and Medicare payments would erase the primary care access gap for Medicaid consumers.

*Preliminary draft. For the latest version: https://sites.northwestern.edu/dab204/

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1 Introduction

In this paper, I examine "lemon dropping" and "cherry picking"[1] with respect to Medicare and Medicaid in the U.S. primary care physician industry. Physicians have financial incentives to favor high payment and low cost patients, especially when capacity is scarce. Medicare and Medicaid are public health insurance programs who regulate payments less generously than private payors. Do physicians respond to these incentives? In a recent survey of the industry, 18 percent of Family Practice and Internal Medicine physicians reported dropping lemons and picking cherries (Page, 2017).

I analyze a unique dataset on the primary care physician population over 2012-2015. I study lemon dropping and cherry picking in two ways with these data. In reduced form models, I use migration as a source of variation in the physician's Medicare-Medicaid regime, and measure the migrant's response to the change in financial incentives. In a structural supply model, I use variation in input-output price ratios and variation in the marginal products of primary care production inputs to estimate the physician cost heterogeneity which drives lemon dropping and cherry picking.

In the reduced form, I find that physicians respond to financial incentives at the margin of patient acceptance. Physicians are more likely to accept more profitable patients. However, I also find that physician idiosyncratic incentives explain most of the variation in patient acceptance. In the structural model, I find that the opportunity cost of physician labor for Medicaid is greater than the cost of labor for Medicare. Moreover, the Medicare opportunity costs of effort and equipment use are most important. I use the model to estimate counterfactual outcomes under competitive pricing. I find that price competition is worse than regulated prices for consumer access because of lemon dropping. I also find that an alternative regulatory regime with equal Medicaid and Medicare payments would erase the primary care access gap for Medicaid.

I begin with a summary of the primary care industry, based on the population microdata. I observe supplier practice locations over time. I measure acceptance of Medicare and Medicaid Dual Eligible patients, and total output capacity for these payors. I also measure physician practice patterns from billing data on the bundle of services supplied, including the labor to capital ratio and the degree of procedural specialization. I match the population microdata to a panel of financial incentives by county, which includes Medicare and Medicaid payment regulations and the local prices of production factors.

I show that there is geographic variation in financial incentives and market size in the

[1] *"A highly colloquial term for the acceptance of patients based solely on their ability to pay–i.e., with insurance or cash–while turning away the indigent or poor."* Segen's Medical Dictionary, 2012.

private payor market as well as in Medicare-Medicaid markets, which are smaller. Primary care physicians are dispersed geographically, and vary in their acceptance rates for Medicare and Medicaid Dual Eligible patients. Financial incentives are related to the distribution of primary care physicians across markets. However, consumer demographics are most important in explaining the cross-section distribution of physicians. I also find that Medicare and Medicaid are rarely the majority of a primary care physician's business.

Physicians vary in the types of patients they accept and also in how they treat accepted patients. The number of procedures offered to Medicare and Medicaid patients varies across locations, and across physicians within a location. Likewise, the labor to capital ratio of procedures supplied varies within and across markets. Capacity for Medicare and Medicaid and output per patient vary significantly, as does the physician's tendency to use an outpatient facility instead of an office to supply equivalent services. There is also heterogeneity in patient demographics across physicians and markets.

From the practice locations data, I find that physician mobility is common, but is declining overtime, as in the general labor market (Molloy, Smith, and Wozniak, 2014). With few exceptions, migrant physicians do not differ significantly from non-movers. Migrants do not disproportionately select more profitable Medicare or Medicaid destinations. Nor is there evidence that primary care movers select destinations with specific practice patterns, beyond a small shift in the mean.

The data suggest that incentives from the private payor market overwhelm those from Medicare and Medicaid in the location decision for physicians who move. Regulation matters after a location is chosen, however. Prices affect the decisions to accept Medicare and Medicaid patients, seemingly to fill slack capacity after serving the privately insured.

Since primary care physician mobility is not associated with financial incentives from Medicare and Medicaid, I ask whether changes in the mover's regulated prices and cost affect acceptance rates for Medicare and Medicaid. I estimate reduced form fixed effects regressions for the subpopulation of physicians who change locations to explain variation in acceptance of Medicare and Medicaid Dual Eligibles, output capacity, and physician practice patterns. In the regressions, I examine two types of exposure from migration. I first estimate regressions with location, physician, and year fixed effects. This specification highlights within-physician variation in payment regulations and local factor prices due to changes between the mover's destination and origin markets. Second, I estimate regressions without location fixed effects, which leaves within-physician variation in incentives and exposure to the broader environment due to migration alone, as in an event study.

The reduced form results with location fixed effects indicate that not every incentive is salient. For instance, I find that the regulator's ten percent revenue bonus for certain zip codes has a statistically significant but economically negligible effect on patient acceptance. In contrast, the Medicare extensive margin[2] is affected by Medicare payment regulation and county factor prices. Sole proprietors react to incentives on this margin differently than group practice physicians. The Medicaid Dual Eligible extensive margin is affected by the Medicaid payment rate, but not by other financial incentives. Results for the intensive margin reveal elastic own and cross-price substitution, consistent with Medicare patients imposing an opportunity cost on the acceptance of Medicaid patients. The patient acceptance results suggest that lemon dropping and cherry picking is the physician's response to costs of capacity which vary by patient-payor type.

Conditional on accepting Medicare or Medicaid patients, I find that total capacity for these payors is not affected by further incentives, except for sole proprietors. However, the allocation of capacity to accepted patients and physician practice patterns do vary with financial incentives. Physicians who accept new Medicare patients as the Medicare price increases are heavier users of equipment without adjusting total output. Suppliers who accept new Medicaid patients as the Medicaid price increases use more labor.

Financial incentives also affect the number of procedures offered by physicians, again with larger responses from sole proprietors. When the Medicare price increases by one percent, physicians on the margin of acceptance have 1.8 more procedures on offer. I find that physician procedural specialization is only affected by variation in costs, and only for group practice physicians.

A code of medical ethics governs the physician-patient relationship. In the code, physicians may refuse a new patient, but it is difficult to dismiss a patient once accepted. Accepted patients must also consent to a physician's practice patterns. Given this code, the practice pattern results are difficult to explain without physician heterogeneity at the acceptance margin. The results are otherwise consistent with the use of practice patterns as commitment mechanisms to avoid unwanted Medicare or Medicaid consumers.

When physicians move, they inherit aggregate market factors beyond regulated payment rates and the local prices of production inputs. A response to the overall environment includes the effects of these financial incentives. I estimate event study regressions without location fixed effects to provide a broader context, and to quantify the relative importance of idiosyncratic incentives to a physician's acceptance policy and practice patterns. The results indicate that environmental factors explain only 45 percent of the change in extensive margin acceptance following migration, and only 22 percent of the change of the intensive margin.

[2]The Medicare extensive margin is measured by an indicator variable for acceptance of Medicare Part B patients. The Medicaid extensive margin is measured by an indicator variable for acceptance of Medicaid Dual Eligible patients. The intensive margin is measured by the log-odds ratio of the Medicaid patient share.

Idiosyncratic physician-patient factors are most important for lemon dropping and cherry picking.

Results in the model with location fixed effects are mixed for outcomes other than the labor to capital ratio and the number of procedures offered. This is not the case in the event study regressions. Exposure to the broader aggregate environment has a similar effect across all outcomes: total capacity, output per patient, facility usage, procedural specialization, the number of procedures offered, and the physician's labor to capital ratio. However, responses to environment can only explain 21-32 percent of the practice pattern adjustment upon migration. As with patient acceptance, idiosyncratic factors including cost heterogeneity are more important than the incentives from regulated payment for physician treatment of the patients they accept.

The reduced form results motivate an analysis of heterogeneity in physician financial incentives. I employ a structural supply model to estimate physician specific opportunity costs of labor, equipment capital, and effort to abate medical malpractice risk. The model exploits several features of the fee-for-service payment contracts used by Medicare and Medicaid.

I model the firm's cost function, the output technology, and assume physicians are price takers who maximize profit. I estimate the primary care production function with input-output data by adapting the methodology of Ackerberg, Caves, and Frazer (2015). The supply model provides physician specific marginal products and necessary conditions from profit maximization which identify heterogeneity in the opportunity costs of variable factors across physicians. This identification approach is similar to that of De Loecker and Warzynski (2012), and De Loecker, Goldberg, Khandelwal, and Pavcnik (2016).

The results of the structural production function indicate that the marginal products of physician labor and effort are most important in primary care. The marginal products of labor and effort are similar in magnitude, with estimated mean elasticities of 0.46 and 0.41, respectively. The marginal contributions of equipment, clinician labor, and medical supplies are an order of magnitude smaller than those of labor or effort. The average estimated marginal product elasticity of equipment is only 0.05. I find wide dispersion in marginal products across primary care physicians.

I employ the structural marginal product estimates in the necessary conditions for profit maximization. I estimate heterogeneity in the opportunity costs of inputs across physicians and across Medicare and Medicaid patients. I focus on Medicare-Medicaid heterogeneity in the opportunity cost of labor. The estimated opportunity costs of labor are dispersed about the market average wage. I find that Medicaid patients have a higher opportunity cost of labor than Medicare.

For treating Medicare patients, I find that the opportunity cost of effort to abate medical malpractice risk is most important. I estimate that the effective cost of effort is always greater than the local medical malpractice insurance premium. The opportunity cost of effort abating malpractice risk is large enough that the effective effort bill surpasses the physician's effective labor factor bill. This bill contrasts with the relatively low regulated payments physicians receive for malpractice risk adjustments.

The estimated opportunity cost of equipment for Medicare is also large. The equipment opportunity cost, relative to its market price, is higher than the opportunity cost of labor. Moreover, equipment costs are more dispersed about the market price than are labor costs. However, when these factor bills are denominated in a common unit, Relative Value Units (RVUs) of output, I find that the effective equipment bill is small compared to labor and effort.

I use the structural estimates to conduct several counterfactuals. Since elder demand for primary care is plausibly inelastic, the supply-side counterfactual is first order. First, I estimate the implied distribution of average variable profit for primary care physicians. The necessary conditions for an optimum yield this metric as a lower bound on average profit. I find the lower bound rent is positive for 76 percent of physicians.

Second, I use the structural estimates to recover each physician's short run average variable cost. I consider a competitive market counterfactual under which primary care is a monopolistically competitive industry. The estimated average variable costs are the counterfactual short run prices that would obtain in this scenario's equilibrium. Estimated average variable cost is widely dispersed across physicians, within and across locations. I find that market prices would fall by 16 percent in the monopolistically competitive scenario. However, because of lemon dropping, physicians would limit access to Medicare and Medicaid Dual Eligible patients. Only 56 percent of physicians would accept Medicare patients, down from 71 percent under current regulated prices.

Third, I consider a competitive market counterfactual under which primary care is a perfectly competitive industry with inframarginal firms. This scenario is motivated by the generality of primary care services, and by dispersion in estimated costs within locations. The predicted counterfactual short run equilibrium price is the highest average variable cost in each market. I find that, on average, county prices would fall by 12.8 percent or $5 per RVU in a short run competitive equilibrium with inframarginal firms. However, there is a thin tail of markets where prices increase upon relaxing regulations. Because of this tail, the counterfactual average variable profit distribution is strictly positive. Yet, because of lemon dropping, perfect competition also reduces mean acceptance rates for Medicare patients, from 71 percent down to 59 percent.

The competitive market counterfactuals suggest that, though there are unintended consequences of price regulations in primary care, the present regulatory environment is better than a competitive environment if the welfare criterion is Medicare and Medicaid consumer access. Finally, I consider the effects of increasing regulated Medicaid payments to equal those of Medicare. I find that Medicaid acceptance rates would rise from 62 percent to 70.7 percent, or nearly the acceptance rate for Medicare. The results imply that equal payments would erase the primary care access gap for Medicaid.

There is a large literature on physician incentives. My contributions are unique and comprehensive data, a novel identification strategy, and results on physician heterogeneity. My results complement a broader literature on healthcare supplier responses to financial incentives, as in Alexander (2017) and Clemens and Gottlieb (2014). The data and findings also contribute to a growing literature on the supply side consequences of geographic variation in healthcare utilization, such as Finkelstein, Gentzkow, and Williams (2016) and Molitor (2016). My structural approach relies on unique microdata, but it complements the literature on the estimation and decomposition of firm heterogeneity using supply-side conditions.

There are several reasons why these results are interesting beyond their contribution to the literature. First, expansion of Medicaid is debated by economists and policy makers as one solution to the failure of health insurance markets, as a means to achieve full population coverage. My results imply that, while Medicaid patients are well insured, the poor design of payment regulations impede these consumers' access to basic healthcare services. As long as physicians have the right to accept or reject individual patients, my results suggest they will respond to financial incentives and avoid taking on new Medicaid patients, expansion or no.

My results also cast light on the objectives of primary care physicians. The main effect of financial incentives is on patient acceptance, and not on physician practice patterns. Indeed, the estimates for practice patterns can be explained entirely by physician heterogeneity on an acceptance margin. My evidence suggests that primary care physicians first do no harm, but also have opportunity costs associated with limited capacity. Physicians respond to those incentives by dropping lemons and picking cherries at the beginning of the physician-patient relationship.

Finally, my results are interesting from the standpoint of market design. I find that regulated payments affect the types of patients a physician accepts, and I find evidence of spillovers from private insurance on who is accepted. If Medicare can make lemons out of Medicaid patients, then private payor cherries can make lemons out of both Medicare and Medicaid patients. As consumers search for primary care services, spillovers across these patients and from the private sector are associated with the rationing of scarce healthcare resources for elder and indigent consumers who place high value on these services.

The remaining sections of the paper are organized as follows. The next section provides an overview of the data and the measures used in this study. There is also an institutional background for primary care physicians, Medicare Part B, and Medicaid Dual Eligible public health insurance. Next, I document notable features of the data, presenting cross-sectional relationships and mobility patterns which motivate the empirical exercises to follow. In Section 4 I present the reduced form models, the role of physician migration and the assumptions necessary for identification, along with the reduced form results. Section 5 describes the structural supply model, the estimates of the primary care production function, and estimates of physician cost heterogeneity. I then present price and profit counterfactuals. I conclude with a discussion of incentives and policy remedies for lemon dropping and cherry picking in the U.S. primary care industry.

2 Physician microdata and measurement

I analyze panel data on the primary care physician population. This section provides an overview of data sources, and my measurement stategy for financial incentives and the characteristics of a physician's medical practice. Details are provided in the appendix. Readers familiar with the Current Procedural Terminology (CPT) coding system, Relative Value Unit (RVU) output metrics, and the fee-for-service payment regulations of the Centers for Medicare and Medicaid Services (CMS) can skip the institutional details without much loss.

2.1 Sources

The physician microdata are constructed from two sources. First, the National Plan and Provider Enumeration System (NPPES) provides a physician population dataset. Physician identities, medical specialties, practice locations, gender, and sole proprietor status are from monthly publications of the NPPES over 2011-2017.[3] Second, 2012-2015 Medicare Physician and Other Supplier Public Use Files provide annual physician billing and patient demographic data. These data contain 100 percent of final-action Medicare Part B non-institutional line items billed for the Medicare fee-for-service population.[4] This includes Medicaid Dual Eligible patients, but not business from private payors.

[3]Thanks to the NBER and Jean Roth for making historical records of these data available. The NPPES is an administrative database created in 2007 by CMS to fulfill mandates of the Health Insurance Portability and Accountability Act of 1996 (HIPAA). It contains the U.S. population of HIPAA covered healthcare providers, including but not limited to the physician population.

[4]In September 2015 a Free of Information Act request was filed with CMS asking that these same public use data be made available for calendar years 2009-2011, but the request was denied by the regulator.

Data on Medicare payment regulations, county costs, and procedure level input-output measures are from various issuances of Physician Fee Schedule Federal Regulation Notices and CMS Relative Value Files over 2011-2017. Data on Medicaid payment regulations are from the Urban Institute in 2014. Last, data on Medicare and Medicaid shares of a physician's total business are from the National Ambulatory Medical Care Survey (NAMCS) over 2011-2014. NAMCS covers public as well as private payor patients. However, it is a small representative subsample of the primary care population, and a repeated cross-section which lacks identifiers for merger to the population microdata panel.

2.2 Primary Care industry

Primary care physicians provide for the general healthcare needs of consumers. From the physician population dataset, I identify primary care by three medical sub-specialties: Internal Medicine, Family Practice, and General Practice.[5] These taxonomies distinguish physicians by their medical training and, to a smaller degree, by the acceptance of children in addition to adult patients.

Primary care is an important industry. The U.S. physician population surpassed 1 million suppliers in 2015, 376,556 of which were identified in the data as primary care. The billing data are sufficient to examine resource allocations in the industry, because Medicare Part B covers all medically necessary services supplied in a physician's office or outpatient facility setting. The data account for $37 billion each year, on average, in payments to primary care physicians for servicing Medicare and Medicaid Dual Eligible patients.

2.3 Measuring financial incentives

Following Clemens and Gottlieb (2014; 2016), I measure Medicare payment generosity via CMS's Geographic Adjustment Factor (GAF). The GAF is a weighted average of Medicare Locality level Geographic Practice Cost Indices (GPCIs), which are themselves derived from county level input factor price data.[6] Details and exact formula are provided in the appendix. In addition to the Medicare payment index, I measure county costs by computing the county level GAF from the underlying factor price data. Last, Medicaid payments

[5]For Internal Medicine, I include both general Internists as well as sub-specialties. Other possible primary care taxonomies include OBYN and Hospitalist physicians, I excluded these latter, small subpopulations to focus on Medicare Part B and to reduce physician heterogeneity.

[6]Medicare Localities are states, and sub-divisions of states with larger populations. Payment GPCIs are regulated as a weighted averages of county level cost indices. Notating counties c in Medicare Locality S, e.g. the regulated price for physician work output is given by "wage GPCI" $= \sum_{c \in S}$ "wage GPCI"$_c * \frac{\text{RVU}_c}{\text{RVU}_S}$, where RVU is the total area output.

are state regulated. I measure Medicaid payment generosity using the Urban Institute's Medicaid conversion ratios and state level averages of the Medicare GAF.

I also examine the differences between sole proprietors and group practice physicians, and the effects of Medicare's primary care physician "bonus" incentives. Physicians receive a 10 percent revenue increase from Medicare for practicing in designated zip codes, which I measure with an indicator variable. Finally, for the structural model I use the GPCIs composing the GAF indices, at the Medicare Locality level for output prices, and at the county level for input factor prices.

2.4 Patient acceptance and demographics

Acceptance of Medicare is measured by merging the primary care population dataset (NPPES) with the Medicare Part B subpopulation billing data, by National Provider Identifier (NPI) number and year. Acceptance of Medicaid Dual Eligible patients is conditional on acceptance of Medicare, by definition of these consumers, and is observed directly in the billing data. Representative Medicare/Medicaid patient demographics are available for each physician-year in the billing data. The data include the fraction each physician's patients who were diagnosed with 16 important diseases. The data contain a measure of overall patient health risk, the Hierarchical Condition Category (HCC) score, an insurer metric for expenditure risk relative to a population average normalized to unity. Also reported is the average age of the physician's accepted patients, and counts by sex and race. Private payor patient demographics are unobserved.

2.5 Measuring practice patterns and output

I measure physician practice patterns from procedural level billings. The data directly contain the number of unique procedures offered, total revenues, and the share of billings in a facility versus an office setting. I measure a physician's procedural specialization, or concentration of billing practices, with the Herfindahl-Hirschman index (HHI) of the bundle supplied using each procedure's share of total billings.[7] I measure output or capacity with "Relative Value Units" (RVUs), the metric used by CMS and many private payors for payment, as well as by Clemens and Gottlieb (2014) and others in the literature. I measure the labor to capital ratio as physician labor minutes per use of equipment. To compute these, I merge the billings data by procedural code (CPT) with the fee-for-service input-output schedule provided in CMS's Relative Value Files.

[7] Thanks to Aviv Nevo for suggesting this practice pattern measure. Notating procedures by k and the observed set of offerings by K, following the standard formula: $\text{HHI} = \sum_{k \in K} (\frac{\text{billings}_k}{\sum_{k \in K} \text{billings}_k})^2$

3 Facts from the data

This section documents several facts regarding variation in financial incentives, patient acceptance, and physician practice patterns. Together they motivate the empirical research question: do physicians respond to financial incentives. I first describe geographic variation in financial incentives. Next I show that county primary care markets vary widely in size, in their number of primary care physicians, and in their fraction of physicians accepting Medicare and Medicaid patients. I then describe geographic variation in practice patterns, and conclude with key facts on physician migration.

3.1 Geographic variation in payment regulation and cost

There is geographic variation in physician financial incentives due to (a) variation in local input factor prices, (b) payment regulations across Medicare Localities, and (c) variation across states in Medicaid payment regulations. Summary statistics from the county distribution of payment policies and cost are provided in Table 1.

The mean Medicare payment index is 0.966 across counties, but has mean 1.016 across 89 Medicare Localities, and mean 1 across the supplier population by construction. The Medicaid payment index has mean 0.729 across counties and mean 0.768 across states. The mean county cost index is 0.925. There is variation in payment across these regions, and variation in cost across counties within region. Variation in Medicaid regulation is pronounced.

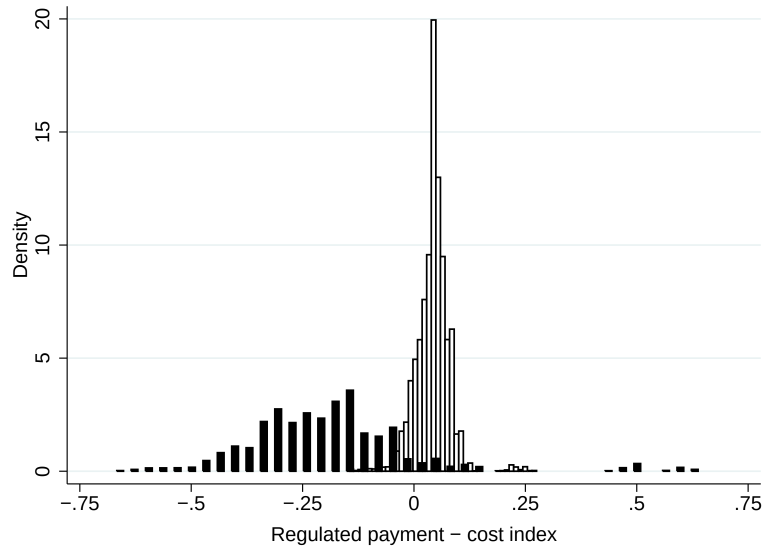
Table 1: Summary statistics of financial incentives

	Mean	St. Dev.	10th %	90th %	N
Medicare payment index	1.016	0.074	0.931	1.123	348
Medicaid payment index	0.768	0.203	0.578	0.969	204
Cost index	0.925	0.051	0.876	0.988	12,473

Notes: Author's calculations from CMS regulation notices. Indices are Geographic Adjustment Factors (GAF), defined in the appendix (8.2.3). N is the number of region-year observations for Medicare Localities, states, and counties, respectively.

Next, I difference the cost GAF from the payment GAF to give a sense of regulated variation in incentives across markets. This profit metric is interpretable as the percentage difference between cost and payment for Medicare because the mean GAF is close to unity. For Medicaid, the metric is interpretable as the percent difference between payment and the opportunity cost of Medicaid relative to Medicare. The empirical density for Medicare and Medicaid across U.S. counties is plotted in Figure 1.

Figure 1: Profit variation for public payors by U.S. county



Notes: The empirical distributions of Medicaid (solid, left) and Medicare (hollow, right) profit indices, defined as the regulated GAF index as percent over local cost (payment − cost)/$\mathbb{E}$(payment). Density is across county-years. Source: Author's calculations from CMS regulation notices.

Figure 1 shows that some counties are more profitable places to accept Medicare and Medicaid patients. It also shows that Medicaid is less generous than Medicare, even accounting for variation in county costs. The opportunity cost of accepting Medicaid in many counties is over 20 percent. The figure illustrates that Medicare regulates prices to provide physicians a small profit, on average. However, many counties are paid below their respective cost index. Few counties have regulated prices 25 percent or more above the average cost of input factors.

In the appendix, I plot the empirical density of the Medicare profit metric across physicians, rather than across counties. Weighting by physicians instead of location symmetrizes the distribution and zeros its expectation. The distinction is due to physician location choices, and is evidence of free mobility.

3.2 Market size and patient acceptance

There is geographic variation in financial incentives. If physicians respond to these incentives, aggregate trends in physician location choice and patient acceptance should evidence it. I exposit four key facts to this end. First, counties vary in market size and physician population. Second, physician acceptance of Medicare patients varies across counties. Third, the aggregate cross-sectional relationship between physician location choice and financial incentives is significant and consistent with competitive entry. Finally, the private payor market is more important than Medicare and Medicaid for location choice.

I measure primary care markets with U.S. counties. There are a several alternative definitions for local healthcare markets.[8]. Counties were chosen for two reasons. First, consumers have long-term relationships with their primary care physician and are unlikely to travel long distances for routine healthcare needs. Traveling beyond county is more common for hospital care or the services of a medical specialist. Second, granularity of the market definition should reflect granularity in primary care physician costs. Counties are the finest available geographic partition of the factor price data. I summarize the size of markets and physician location choices below in Table 2.

Table 2: Primary care county-year market statistics

	Mean	St. Dev.	10th %	90th %
Market size:				
County population[a]	125,610	365,383	6,906	276,163
Medicare[b]	42,502	115,517	266	113,279
Medicaid	10,856	35,290	60	26,449
Number Physicians:				
Total	149	500	2	327
Accept Medicare	106	328	2	243
Accept Medicaid	92	274	1	213
Entry thresholds:[c]				
Population	2,944.6	6,118.9	632.1	5,041.5
Medicare	370.2	184.7	126.8	605.5
Medicaid	109.8	65.2	39	189.3

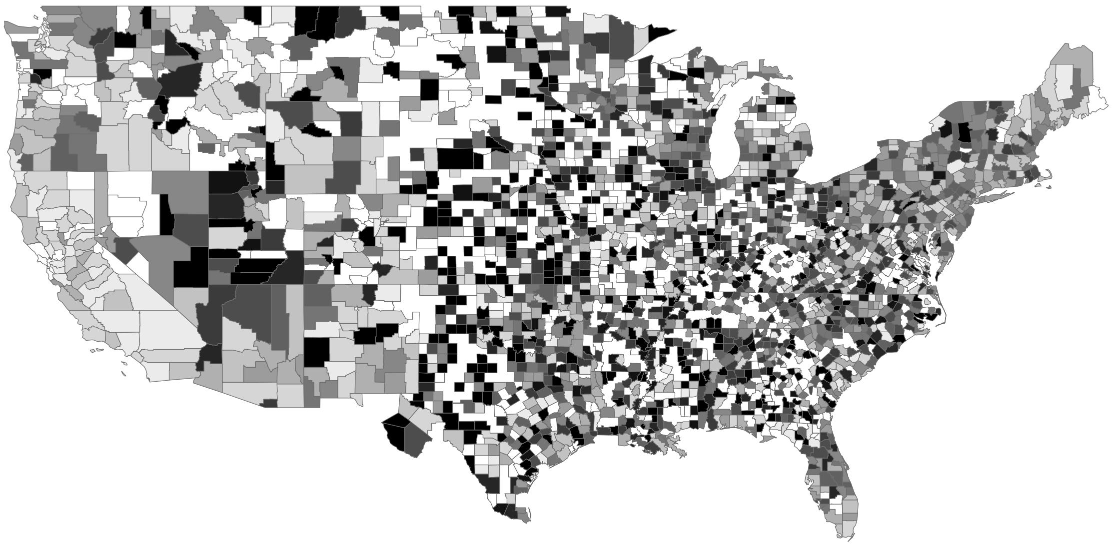
Notes: author's calculations from county aggregates of the physician microdata. [a] Total county population, all ages, from the U.S. Census. [b] Medicare and Medicaid market size is total consumer-physician matches. [c] County consumers per physician, N_c/N_p, by payor type.

Primary care markets vary in size, both in total population and in Medicare and Medicaid subpopulations. The representative market has 149 primary care physicians, though physicians are concentrated geographically. The median county had only 19 physicians; five percent of counties had only one.

Medicare and Medicaid consumers are not accepted by every primary care physician. The mean county had 106 primary physicians accepting Medicare patients, and 92 accepting Medicaid Dual Eligible patients. Only 69.9 percent of physicians saw ten or more Medicare

[8]Alternatives include Hospital Service Areas (HSAs) or Hospital Referral Regions (HRRs) as defined by the Dartmouth Atlas, U.S. states, and Medicare Localities.

Figure 2: Geographic variation in primary care acceptance of Medicare



Notes: Fraction of primary care physicians accepting Medicare in 2014, by county. Lightest areas are 0-10% acceptance, darkest areas are 90-100% acceptance, areas mapped without boarders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.

or Medicaid patients in 2015; ten percent of counties had one or no physicians accepting Medicaid Dual Eligibles.

I illustrate this geographic variation in Figure 2, mapping the fraction of primary care physicians who accept Medicare patients across U.S. counties. Areas in white have less than 10 percent average acceptance, dark black areas have 90-100 percent average acceptance. Grey areas lie between these extremes. The figure illustrates that acceptance of Medicare is dense near large CMS markets, but is not entirely explained by market size. Areas with relatively large elder populations, like Florida or Arizona, have lower Medicare acceptance rates than areas in central Texas.

This suggests a cross-sectional relationship between market size, physician location choice, and financial incentives. To examine this relationship, I define entry thresholds as market size divided by the number of firms in each county each year. When there is competitive entry and supplier homogeneity, as in Bresnahan and Reiss (1991), the threshold measures the ratio of fixed cost to variable profit for the marginal firm. Thus, county entry thresholds should vary inversely with payment incentives in accordance with the physician's variable profit or payoff function.

In the data, entry thresholds vary across locations. The coefficient of cross-sectional variation is largest for Medicare, and smallest for the total population. Markets are tightest for

Medicaid. I regress log entry thresholds on log financial incentives to estimate the elasticity of market tightness with respect to payment rates and cost. I examine the role of financial incentives versus consumer demographics in the cross-section by including county elders' diagnosis rates for 16 diseases, the average age of elders, and the average CMS HCC score to measure of health risk. The elasticity results are reported in Table 3.

Table 3: Primary care physician entry threshold elasticities

Outcome:	Total Population		Medicare		Medicaid	
Medicare payment	-2.011**	-3.537***	-4.187***	-1.312***	-2.181*	0.432
	(.806)	(.497)	(.878)	(.397)	(1.126)	(.407)
Medicaid payment	-0.174	-0.384***	-0.291**	0.177	-0.372*	0.013
	(.114)	(.093)	(.176)	(.079)	(.212)	(.095)
Cost index	-1.614**	3.047***	3.679***	-0.639*	0.830	-2.136***
	(.621)	(.606)	(.707)	(.332)	(.889)	(.363)
Health controls		Y		Y		Y
Year FE	Y	Y	Y	Y	Y	Y
R-squared	0.037	0.3534	0.0649	0.6557	0.0348	0.6391
Observations	9651		9388		9250	

Notes: author's calculations from county aggregates of microdata. Dependent variables are log county consumers minus log county suppliers. Independent variables are log GAF indices. Health controls are county mean disease diagnoses, age, and HCC health risk. Standard errors clustered by Medicare Locality in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Cross-sectional variation in entry thresholds is related first to consumer demographic controls. Disease diagnoses, health risk, and age explain 30-60 percent of between variation in supplier location given market size. Financial incentives are often statistically significant in these regressions, but only explain 3.5-6.5 percent of between variation in county entry thresholds. Where incentives are significant, the coefficients are consistent with variable profit maximization.

For the total population market, variable profits are increasing in Medicare and Medicaid payments rates, and are decreasing in the cost of input factors. Demographic controls are important for the latter result, suggesting a positive correlation between elder health risk and physician average cost. The payment effect is not surprising, even though private prices are not regulated by Medicare or Medicaid. These prices are set individually between private payors and physicians, bargained as a multiple of the local Medicare rate. Clemens and Gottlieb (2017) found that bargained private payor prices are elastic (1.3) with respect to the Medicare price.

Medicare and Medicaid thresholds vary negatively with the Medicare payment rate, when this coefficient is statistically significant. The Medicare rate is more significant economically and statistically than the Medicaid rate in the cross-section. Controlling for demographics, the Medicare threshold is increasing in the Medicaid price. Likewise, the Medicaid threshold is increasing in the Medicare price, however, the relationship is not statistically significant. This result suggests Medicaid presents an opportunity cost of accepting Medicare patients, and vice versa.

Medicare and Medicaid thresholds vary less with payment and cost than do thresholds for the overall market. Demographic controls again are important for this result, though standard errors without controls do not reject equality of the Medicare and overall market coefficients. This fact suggests physician location choices are influenced more by the private payor market than by regulated markets. This is consistent with the next piece of evidence, which shows that Medicare and Medicaid are minority fractions of the physician's total business.

Table 4: Joint density of Medicare and Medicaid revenue shares (NAMCS)

Medicaid→ Medicare↓	0-25%	26-50%	51-75%	76-100%	Medicare margin: (row total)
0-25%	0.343	0.062	0.032	0.003	0.440
	[0.198]	[0.015]	[0.013]	[0.007]	[0.234]
26-50%	0.257	0.072	0.001		0.331
	[0.303]	[0.065]	[0.004]		[0.371]
51-75%	0.001	0.069	0.005		0.075
	[0.200]	[0.008]			[0.208]
76-100%	0.017				0.017
	[0.036]				[0.036]
Medicaid margin:	0.687	0.140	0.033	0.003	
(column total)	[0.737]	[0.088]	[0.016]	[0.007]	

Notes: Frequency of physician revenue shares for Medicare and Medicaid.
Source: National Ambulatory Medical Care Survey (NAMCS) 2011-2014.
Family Practice and [Internal Medicine], sample sizes: 1,476 and [852].
Fraction not reporting revenue shares: 0.136 and [0.151].

For the subsample of the population appearing in the 2011-2014 National Ambulatory Medical Care Survey, I examine the physician's share of business from Medicare and Medicaid. The survey instrument is coarse, soliciting the fraction of revenues in quartile bins from 2,328 physicians. The joint density of respondents across bins is reported in Table 4. I tabulate the data separately for Family Practice and Internal Medicine physicians to illustrate homogeneity in primary care capacity for Medicare and Medicaid, despite differences in medical training and the demographics of non-elder patients.

For most physicians, Medicare and Medicaid are together less than half their business. Medicaid is most negligible. Medicare is a larger fraction of business for Internal Medicine than for Family Practice. This is expected, Family Practice physicians serve a broader patient age range. Assigning unreporting physicians to the right tail of the distribution does not alter the general finding. If assumed in the left tail, Medicare and Medicaid are even less important to the physician's overall business.

3.3 Practice patterns and patient demographics

The primary care population varies in size and in acceptance of Medicare and Medicaid across locations. This variation is related to financial incentives, and also to patient demographics. Now I examine how physicians treat patients once accepted, and the demographics of these consumers using the physician population microdata.

I document several novel facts on primary care practice patterns. The labor to capital ratio, measured by labor minutes per equipment use, varies both across locations and across physicians within a location. There is geographic variation in the procedural specialization of primary care physicians, as measured by the bundle HHI. There is also geographic variation in the physician's tendency to supply equivalent services in an outpatient facility instead of an office setting.

I also document several facts from the population microdata which complement previous research relying on physician subsamples, see Skinner (2011). There is geographic and within location variation in physician capacity for Medicare and Medicaid and in output per patient, as measured by RVUs. There is variation in the number of procedures offered, the number of consumers supplied, and total Medicare and Medicaid Dual Eligible revenue. I begin the exposition with summary statistics from the population in Table 5.

The average primary care physician offers 39 procedures to Medicare and Medicaid Dual Eligible patients. They supply these procedures with relative specialty, the average bundle HHI is 0.29. Facilities are used instead of offices for equivalent services 42 percent of the time. However, 25 percent of physicians always supply in facilities, and 34.7 percent always supply from their office. Average total RVU capacity for Medicare and Medicaid was 3,937 RVUs. Average output per consumer was 9 RVUs.[9] The representative physician has 402 Medicare and Medicaid Dual Eligible patients, on average 26 percent of these are Medicaid.

[9] At the mean price per RVU, $35, this reflects $137,795 in uncensored revenue from the bundle data, or $315 per consumer. This reveals that censoring for privacy concerns affects 86 percent of observed Medicare and Medicaid revenue at the mean.

Table 5: Summary statistics from primary care microdata

	Mean	St. Dev.	10th %	90th %
Practice patterns:				
Number procedures	39.0	31.3	10	80
Labor/capital ratio	22.0	16.5	9.0	47.5
Bundle HHI	0.29	0.21	0.09	0.55
Facility share	0.42	0.43	0	1
Output (RVUs)	3,936.7	5,181.5	302.3	9,363.1
Output per consumer	9.1	7.8	3.2	15.9
Business accounts:				
Medicare revenue ($)	160,073.5	285,460.3	11,267.1	339,591.1
Patients	402.1	452.1	60	835
Medicaid share	0.26	0.21	0	0.55
Accept Medicare	0.71	0.45	0	1
Accept Medicaid	0.62	0.49	0	1

Notes: Author's calculations from physician microdata.
Physician-year observations (2012-2015) in population: 1,441,720.
Practice pattern outcome observations: 956,985 to 1,021,226.

The representative primary care physician supplies 22 physician labor minutes per use of equipment. This ratio varies across physicians and locations, the 90-10 percentile gap being 175 percent of the mean. To illustrate geographic variation in this outcome, in the appendix I map the county average labor to capital ratio. There is similar geographic variation in physician facility usage, in Medicare and Medicaid output, output per consumer, and in the number of procedures offered. I also provide maps of variation in these practice patterns in the appendix.

I find that facility use is heaviest near cities with large low income populations, and in smaller markets that are distant from major metropolitan areas. Geographic patterns in the number of procedures offered to Medicare and Medicaid are similar. Average output for Medicare and Medicaid Dual Eligibles is greatest in the south, in coastal regions with warm weather, and in southwestern metropolitan areas. This is consistent with variation in Medicare market size, due to elder retirement and relocation patterns.

Consumer demographics vary across locations, and were found significant correlates with physician density in the market cross-section. I find the demographics of accepted patients also vary across physicians within a market. I present summary statistics of physician-mean patient demographics in Table 6.

Table 6: Summary of physician mean patient demographics

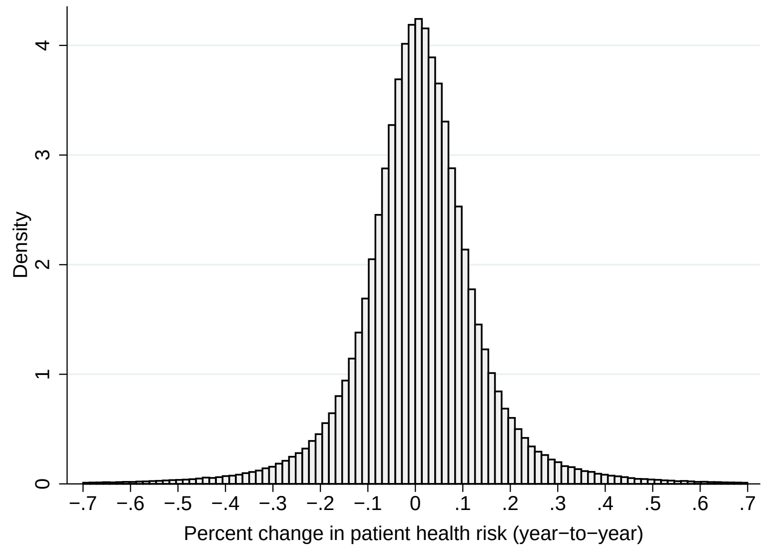
	Mean	St. Dev.	10th %	90th %
Average age	71.51	4.77	66	76
Fraction female	0.55	0.15	0.44	0.62
Fraction black	0.08	0.16	0	0.25
Health risk (HCC)[a]	1.67	0.81	0.95	2.6
Disease diagnosis %:[b]				
Alzheimers	0.13	0.12	0	0.29
Arthritis	0.39	0.13	0.26	0.53
Asthma	0.09	0.08	0	0.18
Atrial fibrillation	0.13	0.10	0	0.28
Cancer	0.11	0.10	0	0.18
Depression	0.25	0.13	0.11	0.42
Diabetes	0.37	0.15	0.21	0.55
Heart failure	0.26	0.18	0	0.52
Hyperlipidemia	0.56	0.15	0.38	0.75
Hypertension	0.68	0.12	0.54	0.75
Ischemia	0.40	0.18	0.2	0.67
Kidney disease	0.30	0.18	0.11	0.57
Obstructive pulmonary	0.20	0.14	0	0.39
Osteoporosis	0.08	0.07	0	0.16
Schizophrenia	0.05	0.07	0	0.12
Stroke	0.06	0.06	0	0.15

Notes: Author's calculations from physician microdata.
[a] CMS's Hierarchical Condition Category score.
[b] Physician diagnoses rates are censored above by 0.75.

Physicians are diverse in the patients they accept. The representative physician's average Medicare and Medicaid Dual Eligible patient is 71 years old. Patient health risk is above the population average, as expected from an expectation conditional on positive expenditure. The most common disease diagnosis is hypertension. Ischemic heart disease, arthritis, diabetes, and depression are also common.

There is substantial variation across physicians in their accepted patient's diseases and overall health risk, evidenced by the coefficients of variation in disease fractions and HCC score. Though physician-patient relationships are thought to be persistent, there is also significant within-physician variation in patient average health. That is, the data suggest there are idiosyncratic patient health shocks. To illustrate this, I compute the physician's year-over-year change in log HCC score. I plot the empirical distribution of the health shocks measure in Figure 3.

Figure 3: Empirical density of patient health shocks



Notes: Health shocks measured as year-over-year change in the log of a physician's average patient health risk (HCC) score. Source: Author's calculations from physician microdata.

3.4 Physician migration

I now describe patterns in primary care physician geographic mobility from the microdata. There are three novel facts to document. First, fifteen percent of physicians migrated across counties over 2011-2015, with mobility declining over time. Second, the demographic differences between movers and non-movers are small. Third, migration flows are bi-directional. Thus, the migrant's change in environmental factors is symmetrically distributed, mean zero for payment regulations and cost, and near mean zero for practice patterns and patient acceptance. I illustrate the first of these facts in Table 7.

Table 7: Primary care physician population and migration by year

	2011	2012	2013	2014	2015	Total
Population	332,219	343,874	355,178	366,112	376,556	385,561
Movers	14,172	14,065	13,383	12,865	12,843	58,756
% movers	4.27	4.09	3.77	3.51	3.41	15

Notes: Author's tabulations from physician microdata.

There were 376,556 physicians designated as general Internal Medicine, Family Practice, General Practice, or an Internal Medicine sub-specialty in 2015. This supplier population grew 13.3 percent from 2011-2015, about 2.7 percent annually. There were 385,561 unique primary care physicians over the horizon, showing attrition and new entry in the population. Each year 3.4-4.3 percent of primary care physicians move counties, a small fraction moved twice. The mobility rate fell each year, declining twenty percent over the period. 15 percent of the population moved counties, however, every move was not across a Medicare Locality or state line.

Movers and non-movers are similar in most dimensions. Appendix Table 8.3.1 reports summary statistics across the two groups. Because these are populations, there is no sampling error in the means, and the true standard deviations are known.[10] To examine whether the differences are meaningful, I normalize means by standard deviations and compute the difference in standardized scores. None of the scores are statistically significant at a usual level. The representative mover is within 60 percent of a standard deviation of the representative non-mover for ever measure. Most differences are within ten percent of a standard deviation.

However, there are four differences to highlight. Movers were more often women, by a nine percentage point difference in population gender means. They were more likely to be general Internists. Movers also had smaller businesses, by 83 patients and about $54,500 in revenue. Finally, migrants were more likely to use facilities.

Table 8: Summary of mover's change in environmental factors

	Mean	St. Dev.	10th %	90th %
Practice patterns:				
Δ log(# procedures)	0.04	0.34	-0.36	0.47
Δ log(labor/capital)	-0.03	0.21	-0.24	0.19
Δ log(bundle HHI)	-0.02	0.23	-0.30	0.25
Δ facility fraction	-0.02	0.18	-0.25	0.20
Δ log(output (RVUs))	0.04	0.54	-0.58	0.66
Δ log(output per consumer)	0.01	0.26	-0.25	0.26
Business environment:				
Δ log(Medicare revenue)	0.01	0.26	-0.28	0.30
Δ Medicare acceptance rate	0.01	0.08	-0.09	0.10
Δ Medicaid fraction	-0.01	0.09	-0.12	0.10
Δ log(health risk)	-0.03	0.16	-0.23	0.17
Δ log(Medicare price)	0.00	0.07	-0.09	0.07
Δ log(Medicaid price)	0.00	0.16	-0.17	0.18
Δ log(cost index)	0.00	0.07	-0.09	0.08

Source: Author's calculation from physician microdata.
Variables are the destination - origin difference in county means.

When physicians migrate, they inherit new environmental factors in their destination. This includes new financial incentives in payment regulations and input factor costs. It

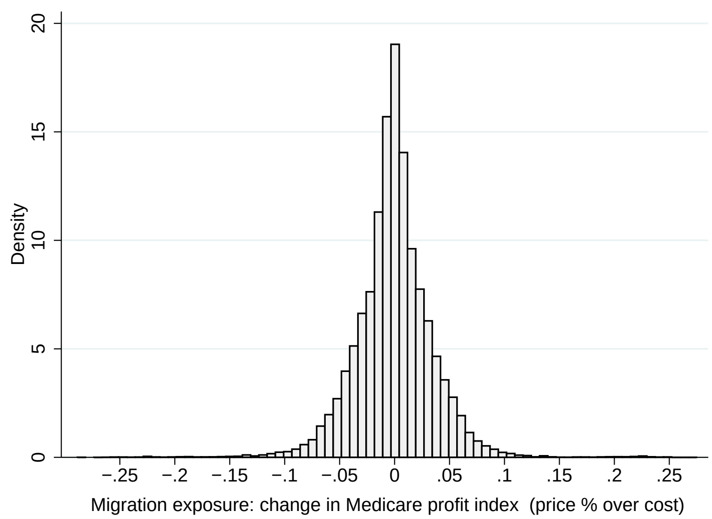
[10]A caveat applies to disease fractions, which are censored for privacy concerns from above at 0.75 and from below if fewer than 11 of the physician's patients were diagnosed.

also includes new county average practice patterns, and the Medicare-Medicaid acceptance policies of other local physicians. I now document facts on the distribution of changes in environmental factors. Table 8 reports summary statistics on destination-origin changes for the migrant subpopulation.

The distributions are symmetric, due to bi-directional migration flows. The mean percent change in financial incentives was zero. Mean changes in patient acceptance and other county business environment measures are near zero. The distribution of changes in the county profit index, as previously defined in Figure 1, illustrates exposure to new financial incentives.

In Figure 4, I plot the histogram of changes upon migration in Medicare payment minus county cost. This figure shows that migrant destination choices are not driven by Medicare rent seeking. If Medicare's financial incentives were an important factor in location choice, the density would be left skewed. I find no evidence of skew.

Figure 4: Empirical density of mover's change in Medicare financial incentives



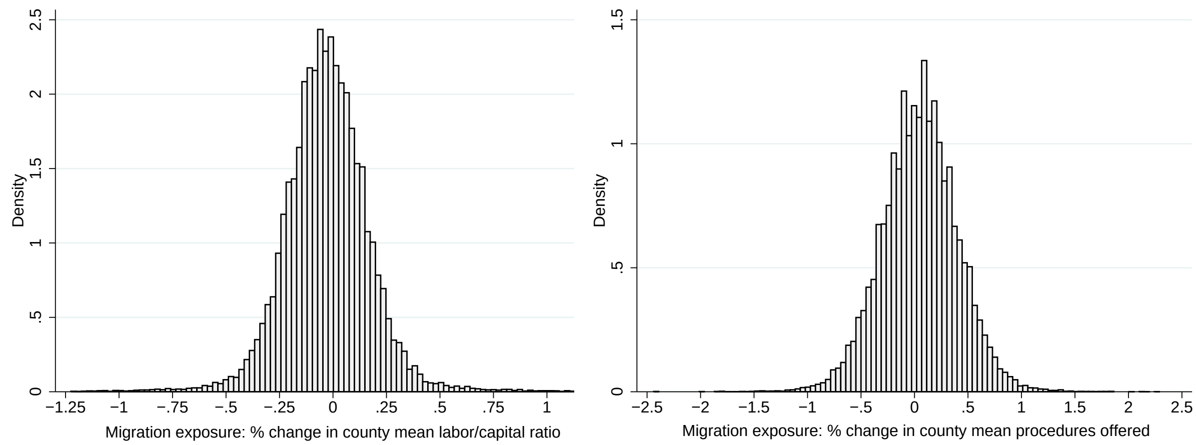
Notes: Change across county moves in the Medicare price as a percent of local cost, measured by (payment − cost)/$\mathbb{E}$(payment). Source: Author's calculations from physician microdata.

Mean changes in the practice pattern environment were larger. On average, movers entered counties where physicians offered four percent more procedures and supplied four percent more total output to Medicare and Medicaid. The destination county's labor to capital ratio was three percent lower, and average bundle specialization two percent lower, on average.

Growth in mean county practice patterns can suggest relocations are rent seeking. However, this interpretation is not supported by mean growth in regulated payment rates and local costs. Nor is this argument supported by mean growth in county average revenues, by mean differences in Medicare and Medicaid patient acceptance rates, or by mean growth in county output per patient.

The distribution of changes in environmental practice patterns illustrates this point for financial incentives. In Figure 5, I plot empirical densities of the percent change in county average labor to capital ratios, and of the percent change in county average procedures offered. For the interested reader, the appendix provides histograms for Medicare acceptance and for other practice patterns. Figure 5 shows that changes in environmental practice patterns are symmetrically distributed and, while not mean zero, are near mean zero.

Figure 5: Empirical density of mover's change in environmental practice patterns



Notes: Change across county moves in log labor minutes per equipment use (left), and log number of procedures offered (right). Source: Author's calculations from physician microdata.

3.5 Summary of facts

There is geographic variation in financial incentives and market size, both in the private payor market and in the smaller regulated price markets of Medicare and Medicaid. Primary care physicians are dispersed geographically, and vary in their acceptance rates for Medicare and Medicaid Dual Eligible patients. Financial incentives are significantly related to the distribution of primary care physicians across markets. However, consumer demographics are most important in the cross-section. Medicare and Medicaid are small fractions of the representative primary care physician's business.

Primary care physicians vary both in the types of patients they accept, and in how they treat accepted patients. The number of procedures offered to Medicare and Medicaid patients varies across locations, and across physicians within a location. Likewise, the labor to capital ratio of procedures supplied varies within and across markets. Capacity for Medicare and

Medicaid and output per patient both vary significantly, as does the physician's use of an outpatient facility instead of an office setting to supply services.

Physician mobility is common, 15 percent of the population moved between 2011-2015. With few exceptions, migrant physicians are not different from non-movers. Migrants do not select more profitable Medicare or Medicaid destination counties. There is little evidence primary care movers select destinations with specific practice patterns.

The facts indicate that lemon dropping and cherry picking is a story of acceptance. Financial incentives impact the distribution of primary care physicians across locations, but consumer demographics are most salient. For market selection, incentives from the private payor market overwhelm those from Medicare and Medicaid. Regulation matters after entering a location. Price controls affect the decisions to accept Medicare and Medicaid Dual Eligible patients, to fill slack capacity left from serving the privately insured.

These basic facts motivate a more formal analysis of the microdata. I ask: do physicians respond to financial incentives and refuse low payment patients? In answer, I now examine lemon dropping and cherry picking through the lens of a reduced form supply model. I include a rich set of patient demographics in addition to physician and year fixed effects. I first estimate the model also with location fixed effects, exploiting physician migration to identify the coefficients on financial incentives for outcomes of patient acceptance and practice patterns. I then extend the model, using its implied structure on county aggregates, to an event study framework and estimate the migrant's response to broader environmental factors. These models, their identification, and the results are exposited in the next section.

4 Reduced form models

4.1 Effects of incentives: estimation and identification

I index physicians by j, county locations by r, and time periods by t. Markets are thus indexed (r, t), and the set of suppliers therein by $j \in J_{rt}$. I assume a partial linear model relating the physician's outcome y_{jrt} to financial incentives z_{rt}, observable controls x_{jt}, separable unobservable fixed effects γ_j specific to the physician, γ_r effects specific to the location r, and γ_t effects specific to the year. Formally, I assume

$$(1) \qquad y_{jrt} = z_{rt}\rho + x_{jt}\beta + \gamma_j + \gamma_r + \gamma_t + B(\mathcal{P}_{jt}) + e_{jrt}$$

where e_{jrt} is the model's residual, and $\mathcal{P}_{jt}$ is the probability physician j chose destination r given her location in the previous period $t-1$.

I consider three alternatives for the location fixed effect, each leaves different identifying variation in the data for ρ. First, I consider county fixed effects. This strategy leaves exposure to financial incentives from within physician changes in z_{rt}, induced by migration *and* changes over time in the regulated payment rate. Second, I consider Medicare Locality fixed effects, which leaves more variation between counties to identify the cost effect. Finally, I consider the case of no location fixed effect, and instead include a control for county market size: log Medicare consumers.

The control function $B(\mathcal{P})$ addresses selection bias in physician mobility. Potential sources of endogeneity are unobserved variables affecting capacity for and treatment of Medicare and Medicaid patients, including the physician's unobserved private payor business. Physicians may select locations with foresight of these unobserved variables. While facts from the previous section indicate selection bias should be small, firm migration is a choice to exit one market and enter another. Ignoring this confounds a causal interpretation of ρ.

Conditional discrete choice probabilities are sufficient data to purge (1) of this bias, an insight due to Lee (1983) and related to Hotz and Miller (1993).[11] Because county migration flows are voluminous, I estimate $\mathcal{P}(r', r)$ nonparametrically for each county pair (r', r). I then assign $\mathcal{P}_{jt} = \mathcal{P}(d(j,t), o(j, t-1))$ given the physician's destination $d(j,t)$ and origin $o(j, t-1)$. The function $B(\mathcal{P})$ is nonparametrically identified. However, I take a semiparametric approach similar to Dahl (2002), estimating a flexible sieve for B simultaneously with the linear parameters.[12]

Physician migration is key to identifying ρ. There is little time series variation in financial incentives z_{rt}. A full set of fixed effects $(\gamma_j, \gamma_r, \gamma_t)$ is an ideal control for unobserved physician idiosyncrasies, including productivity, unobserved market factors broader than financial incentives, and secular trends in outcomes. County fixed effects strip away most variation in incentives z_{rt}. For physicians who migrate, there is within variation in $z_{rt} - z_{r't-1}$ due to the policy change between periods. Identification of demographic coefficients β is otherwise standard, noting migration contributes important variation in x_{jt} when new physician-patient matches form.

The final identifying assumption for (1) is strict exogeneity of the residual e. In words, I assume that price regulations and input factor prices are exogenous conditional on the fixed effects. Formally,

$$\mathbb{E}(e_{jrt} | z, x, \mathcal{P}, \gamma) = 0$$

where omission of indices for $(z, x, \mathcal{P}, \gamma)$ is intensional. This makes explicit that e_{jrt} is mean

[11] With discrete choices, the expectation of the residual is a (possibly unknown) monotone function of conditional choice probabilities, i.e. $B(\mathcal{P}(r', r)) \propto \mathbb{E}(y_{jr't} - z_{r't}\rho - x_{jt}\theta - \gamma_j - \gamma_{r'} - \gamma_t | j \in J_{r't}, j \in J_{r,t-1})$.

[12] I estimate a 5th order polynomial sieve for each year relative to the migration year and non-migration, resulting in 40 parameters to be estimated for $B()$.

orthogonal to contemporaneous observables as well as to leads, lags, spacial perturbations, and all fixed effects. This is a strong but common assumption in linear panel regression, as in Wooldridge (2010). It is not directly testable. However, individual primary care physicians are insignificant in the regulator's calculus, and are likely unimportant to the equilibrium of local factor markets. Any first order bias is thus selection bias, already purged by $B(\mathcal{P})$.

4.1.1 Financial incentives affect patient acceptance

I estimate (1) with three measures y of patient acceptance. For extensive margins, I take indicators for acceptance of any Medicare Part B or Medicaid Dual Eligible consumers as patients. To measure the intensive margin, I take the log-odds ratio of the Medicaid/Medicare patient mix. Financial incentives z include levels of the Medicare, Medicaid, and cost GAF indices. I include an indicator for sole proprietorship and its interaction with payment and cost. I also report the effects of Medicare's ten percent revenue "bonus." Standard errors are clustered at the physician level. I report the main results in Table 9.

To interpret these results, first consider column 1 and the physician's bargaining problem with private payors. Prices paid by private insurers are negotiated as a multiple of the local Medicare rate. The literature suggests that Medicare has an elastic (1.3) pass-through effect on bargained private payor prices (Clemens and Gottlieb, 2017). Holding capacity fixed, this implies a physician's private payor profit will increase more than Medicare profit as the regulator increases prices across localities. As profit from private payor patients goes up, the opportunity cost of capacity for Medicare and Medicaid increases . The acceptance rate will fall if firms in the industry are near total capacity. This is not testable using observed capacity for Medicare and Medicaid Dual Eligibles, since total capacity is unobserved.

Whether or not physicians are capacity constrained, if there is imperfect information in the negotiation with private payors, then physicians can improve their bargaining position by keeping costs private information. Since bargained profits are elastic in the Medicare price, the information incentive presents another increasing opportunity cost of acceptance. Private payors receive a public cost signal when a physician accepts Medicare and Medicaid, because average cost must be at least as low as the regulated price. Which incentive dominates depends on Medicare as a fraction of the physician's business. If this faction is small, the opportunity cost outweighs potential gain, and physicians will be less likely to accept Medicare and Medicaid.

The results in column 1 and the facts of the previous section are consistent with an opportunity cost of capacity interpretation. For physicians in group practices, Medicare Part B acceptance is negatively related to the Medicare payment rate and positively related to the county's cost index. The results imply group practices have higher opportunity costs of Medicare acceptance than sole proprietors.[13] For solo physicians, this suggests either distance from a capacity constraint, or a lack of bargaining power with private payors. Sole proprietors are also less likely to accept Medicare in high cost areas. Otherwise, sole proprietors do not differ significantly on average from physician groups in their acceptance of Medicare or Medicaid Dual Eligible patients.

Table 9: Affects of financial incentives on patient acceptance

Acceptance outcome:	Medicare ext. margin	Medicaid ext. margin	Medicaid log-odds
Selected covariates:			
Elder health risk	NA	-0.0648***	0.0948***
		(0.00163)	(0.00297)
(SP) Sole proprietor	-0.0353	-0.0279	0.0466
	(0.0492)	(0.0388)	(0.0689)
10% payment bonus	0.00770**	-0.00101	0.0114***
	(0.00316)	(0.00269)	(0.00413)
Financial incentives:			
Medicare payment	-0.390***	-0.0452	-1.937***
	(0.0955)	(0.0850)	(0.126)
Medicaid payment	0.141	0.573***	3.540***
	(0.170)	(0.148)	(0.217)
Cost index	0.0897***	-0.00729	-0.384***
	(0.0321)	(0.0288)	(0.0405)
SP-financial interactions:			
Medicare payment	0.276***	0.0175	-0.173*
	(0.0706)	(0.0635)	(0.100)
Medicaid payment	-0.0435*	0.0122	0.00242
	(0.0240)	(0.0186)	(0.0313)
Cost index	-0.268***	-0.0120	0.141*
	(0.0609)	(0.0550)	(0.0843)
Observations	1,340,159	866,343	774,470
R-squared	0.011	0.257	0.614
Mean outcome	.709	.871	-1.019

Notes: author's calculations from physician microdata. Financial incentives are levels of GAF indices, defined in appendix 8.1.3. All regressions include physician, county, and year fixed effects. Columns 2 and 3 include consumer disease and demographic controls, these controls are unavailable for physicians who do not accept Medicare. Std. errors clustered by physician in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

[13]Because of fixed effects, identification of the sole proprietor effect is off physician flows in and out of group practice.

The Medicaid extensive margin is measured conditional on acceptance of Medicare Part B. Referring to column 2, as Medicaid payments go up physicians are more likely to accept Medicaid. For physicians at the extensive margin, the mean county Medicaid population share is 17.35 percent. For these physicians, equating Medicare and Medicaid payment rates adds 20.18 percentage points to the extensive margin, on average. The mean Medicaid patient share is 26.2 percent across the population. Together, these numbers imply that equalizing Medicaid and Medicare payments would induce acceptance of Medicaid from the extensive margin up to the county population share, and up to 72 percent of the mean physician patient mix.

On the intensive acceptance margin, physicians are elastic with respect to payment rates. I examine intensive substitution patterns using the log-odds ratio of the Medicaid patient mix.[14] The results in column 3 are interpretable as a logit model for acceptance of Medicaid. The model predicts own and cross price elasticities for Medicaid acceptance consistent with revenue and opportunity cost incentives. When Medicaid rates increase, physicians are more likely to accept these patients. The mean predicted own price elasticity is 1.77. When Medicare rates increase, Medicaid is less likely to be accepted. The mean predicted cross price elasticity is -1.46. The 93rd percentile of the cross price elasticity distribution is -1, and the 96th percentile of the own-price elasticity distribution is +1.

The cost effect in the logit model is an order of magnitude smaller than the payment effect. When costs increase, acceptance of Medicaid is less likely, consistent with profit maximization. The effect of Medicare's physician bonus program is statistically significant but economically negligible. The ten percent revenue bonus is worth only 0.7 percentage points on the Medicare extensive margin. From column 3, this bonus increases the Medicaid-Medicare odds ratio by only one percent.

4.1.2 Financial incentives impact practice patterns

Next, I estimate (1) with (log) physician practice pattern outcomes for y. I report results for the number of procedures offered, the labor to capital ratio of treatments supplied, total Medicare-Medicaid output (RVUs), and the physician's degree of specialization, as measured by the HHI of the bundle supplied. Other practice patterns are reported in the appendix. I measure incentives z with (log) payment and cost GAFs, include interactions with sole proprietorship, and a dummy for Medicare physician bonus zip codes. The payment and cost effects are interpretable as elasticities, reported in Table 10.

I find that the number of procedures offered is increasing in the Medicare price, decreasing in the Medicaid price, and decreasing in local average cost. Payment responses are elastic,

[14] Physicians with no Medicaid or all Medicaid patients are excluded from the intensive margin regression.

and more so for sole proprietors. As the Medicare GAF rises by one percent, physicians on the acceptance margin taking new patients have 1.8 additional procedures on offer at the mean. Physicians are less elastic with respect to cost. The cost effect is not statistically significant for physicians in group practices, but is significant for solo physicians. Sole proprietors are smaller operations, on average having 6.4 percent fewer procedures on offer compared to group practices. The ten percent revenue bonus has no effect on the number of procedures offered.

The primary care labor ratio elastically relates to financial incentives. However, the most significant determinants of the labor to capital ratio are the diseases and demographics of a physician's patients. These factors, consumer health risk in particular, contribute most to the exceptional fit of the linear regression. Referring to column 2, when the Medicare price goes up, primary care physicians accepting new patients are those who use more equipment, lowering the labor to capital ratio 3-to-1. When the Medicaid price increases, physicians accepting new Medicaid patients use less capital relative to labor, raising the labor to capital ratio 3-to-1. The results imply that a one percent increase in Medicaid payment is worth 40 additional seconds of physician labor per equipment billing at the mean, an economically small effect.

As local area costs increase, primary care physicians are more likely to use equipment than their own labor. The cost elasticity is an order of magnitude smaller than both payment elasticities. Additionally, sole proprietors are more likely to use labor relative to capital, also worth 40 seconds of labor per equipment billing at the mean. However, solo physician labor ratios do not relate differently to financial incentives than group practice physicians. Again, the ten percent revenue bonus has no effect.

Conditional on acceptance of Medicare and Medicaid, the physician's total output is not significantly affected by financial incentives. One exception is notable: sole proprietors on the margin who accept new patients as the Medicare price increases have more slack capacity. The output result is interpretable as a horizontal supply response, with sole proprietors at the margin. Total capacity for Medicare and Medicaid Dual Eligibles is inherited from the physician's business with non-elder patients. A group practice's capacity for Medicare and Medicaid is driven by factors other than payment regulation, including the generosity of private payors. Sole proprietors are smaller businesses with less capacity, and so have higher returns to expanding capacity for new Medicare and Medicaid patients.

Table 10: Impact of financial incentives on practice patterns

Outcome:	# Procedures offered	Labor/Capital ratio	Output (RVUs)	Bundle HHI
Selected covariates:				
Medicaid share	0.0740***	-0.0617***	0.204***	-0.0831***
	(0.00824)	(0.00947)	(0.0148)	(0.00767)
Elder health risk	-0.139***	0.168***	-0.201***	0.130***
	(0.00314)	(0.00399)	(0.00612)	(0.00318)
(SP) Sole proprietor	-0.0635***	0.0299**	-0.0740***	0.0318**
	(0.0127)	(0.0137)	(0.0203)	(0.0127)
10% payment bonus	-0.000274	-0.00272	-0.00196	0.0103**
	(0.00522)	(0.00706)	(0.00916)	(0.00520)
Elasticities:				
Medicare payment	4.674***	-3.034**	0.228	-1.058
	(1.064)	(1.278)	(1.265)	(1.374)
Medicaid payment	-4.061***	3.100**	0.611	0.910
	(1.059)	(1.266)	(1.256)	(1.370)
Cost index	-0.0500	-0.354***	0.0164	0.247***
	(0.0498)	(0.0812)	(0.0769)	(0.0522)
SP Elasticity ↑:				
Medicare payment	0.223*	-0.126	0.406**	0.132
	(0.122)	(0.159)	(0.184)	(0.122)
Medicaid payment	-0.0560**	0.00839	-0.00776	0.0143
	(0.0268)	(0.0291)	(0.0431)	(0.0266)
Cost index	-0.200*	0.0970	-0.258	-0.220**
	(0.104)	(0.136)	(0.158)	(0.103)
Observations	869,403	831,514	855,800	861,465
R-squared	0.115	0.342	0.303	0.091
Mean exp(outcome)	39.9	33.8	3985.6	XX

Notes: author's calculations from physician level panel, see appendix. Dependent and financial variables are in logs. All regressions include physician, county, and year fixed effects; and consumer disease and demographic controls. Standard errors clustered at physician level in parenthesis; ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Referring to column 4 in Table 10, to the extent that primary care physicians specialize, sole proprietor are more likely to specialize. Otherwise, cost incentives matter, and only for group practice physicians. Payment regulations have no association with specialization, consistent with the findings of Gottlieb et al (2010). Physician bonuses have a statistically significant but economically small, positive effect on specialization.

4.1.3 Summary

In the microdata, results from the movers regressions confirm that lemon dropping and cherry picking occurs at the front end of the physician-patient relationship. The Medicare extensive margin is affected by Medicare payment regulation and county factor prices. Sole proprietors internalize incentives on this margin differently from group practice physicians. The Medicaid Dual Eligible extensive margin is affected only by the Medicaid payment rate. The estimated effects tell a story of profit maximization with opportunity costs of capacity which vary by patient type. Temporary revenue bonuses for rural zip codes have statistically significant but economically meaningless effects on patient acceptance.

Likewise, how physicians treat accepted patients is associated with financial incentives, but results depend on the outcome analyzed. Total capacity for Medicare and Medicaid Dual Eligible patients is unchanged by payment regulations and cost, save for sole proprietors. A horizontal supply curve supports an inherited capacity interpretation, with sole proprietors composing an upward sloping margin of firms. Without affecting total output, the labor to capital ratio of supplied treatments varies with payment rates, also with larger elasticities from sole proprietors.

I interpret the results for practice patterns as a composition effect: physician heterogeneity acting through the acceptance margin. As Medicare prices increase, physicians accepting new Medicare patients are more likely to be users of capital and more likely to have a wider variety of procedures on offer. Sole proprietors accepting new patients as the Medicare price increases are more likely to have slack capacity.

As similar composition story explains results for the significant relationship between financial incentives and the number of procedures offered by physicians. Physician procedural specialization is only associated with variation in costs, and only for group practice physicians. An alternative interpretation to a composition affect acting through patient acceptance has strong implications. The results would imply physicians use practice patterns as commitment mechanisms to avoid unwanted Medicare or Medicaid consumers.

Financial incentives from Medicare and Medicaid are not the only environmental factors that change when physicians migrate. Movers inherit new patient demographics, professional peers, characteristics of the private payor market, and other features of the destination's healthcare institutions. I now exploit physician migration and an extension of model (1) to examine the physician's response to broader environmental factors. The results give context for the response to financial incentives.

4.2 Event study: estimation and identification

The canonical event study model follows from the linear decomposition of market aggregate outcomes implied by model (1). Additivity teases the first order contribution of broader environmental factors, all mean variation in the market cross-section r, from individual effects, all mean variation in the j cross-section. The expectation of (1) conditional on county r provides

$$\overline{y}_r = \overline{x}_r\theta + \mathbb{E}(\gamma_j | j \in J_r) + \overline{z}_r\rho + \gamma_r = \overline{\gamma}^p_r + \overline{\gamma}_r$$

There are two aggregate terms. $\overline{\gamma}^p_r := \overline{x}_r\theta + \mathbb{E}(\gamma_j | j \in J_r)$ is derived from the market's distribution of physician idiosyncrasies and patient match effects. Environmental factors[15] are together in $\overline{\gamma}_r := \overline{z}_r\rho + \gamma_r$.

The migrant's exposure to environmental factors is defined as the destination-origin difference in aggregates:

$$\delta_j := \overline{y}_{d(j)} - \overline{y}_{o(j)} = (\overline{\gamma}^p_{d(j)} - \overline{\gamma}^p_{o(j)}) + (\overline{\gamma}_{d(j)} - \overline{\gamma}_{o(j)})$$

I use leave-out means when measuring δ to avoid a mechanical form of measurement error. I estimate the physician's response for each period of "event time" $\tau \in \{-3, -2, -1, 0, 1, 2, 3\}$, which tracks the calendar year relative to the date of migration. Though outcomes data are available only for four periods, 2012-2015, I can estimate three pre and post migration period effects because the physician locations panel is longer, 2011-2017.

I define S_τ as the mover's mean response to exposure δ in relative move year τ. Because y and δ have identical units, S_τ is a unitless effect. Pre-post migration differences $\mathbb{E}(S_\tau | \tau > 0) - \mathbb{E}(S_\tau | \tau < 0)$ are interpretable as the expected percent change in a mover's outcome due to the change in environmental factors upon migration.

Substituting the definition of δ_j into (1) through the county fixed effect, the reduced form model may be rewritten as an event study:

$$(2) \qquad y_{jrt} = x_{jt}\theta + \sum_{\tau=-3}^{3} S_\tau * 1(t=\tau)_j * \delta_j + \sum_{\tau=-3}^{3} \gamma_\tau * 1(t=\tau)_j + \tilde{\gamma}_j + \gamma_t + B(\mathcal{P}_{jt}) + \tilde{e}_{jrt}$$

The residual $\tilde{e}_{jrt}$ includes physician specific heterogeneity in the environmental response, and physician fixed effects $\tilde{\gamma}_j$ control for the migrant's origin. The new terms γ_τ are relative move year fixed effects, and an indicator function $1(t=\tau)$. The control function for selection bias $B(\mathcal{P})$ is as in (1).

[15]Including but not limited to regulation, local input factor prices, and the private payor market

The identifying assumption for (2) is also strict exogeneity. Formally,

$$\mathbb{E}(\tilde{e}_{jrt}|x, \delta_j, \tau, \mathcal{P}, \gamma) = 0$$

In words, I assume exposure to environmental factors is exogenous conditional on the relative migration year, observables, and fixed effects. Two subtle assumptions are embedded in this condition: the migration year and physician heterogeneity in the environment response are conditionally exogenous.

The reduced form (2) generalizes a difference-in-differences identification strategy. Any systematic differences between movers and non-movers will be apparent in the pre and post move dynamics of S_τ. A parallel trends assumption is not required. However, if the data support this assumption then S_τ will be constant over $\tau < 0$, jump upon migration, and persist at the higher level for $\tau > 0$. Pre and post-move adjustments in S_τ are evidence of physician adaptation to environment.

4.2.1 Response to environment: patient acceptance

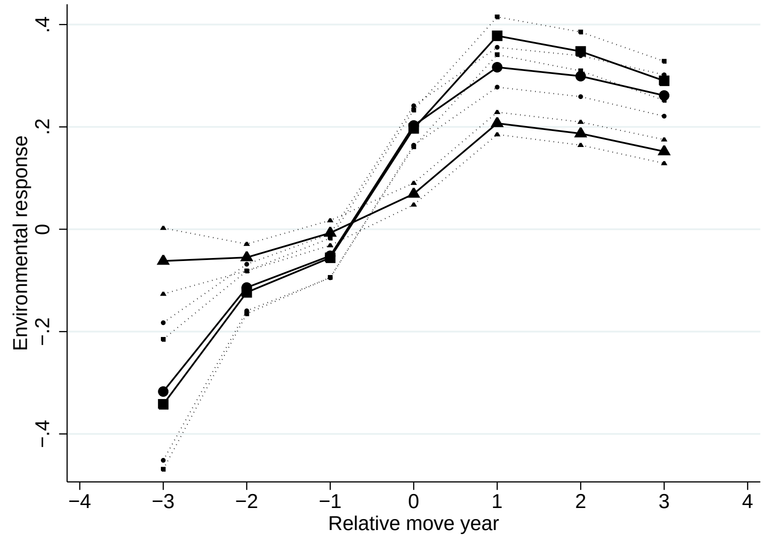
I first examine the response of patient acceptance to the broader market environment. I estimate (2) with indicator outcomes for acceptance of Medicare and Medicaid Dual Eligible patients, and for the Medicaid fraction of accepted patients. I also analyze the response of the physician's average patient health risk and the physician's facility usage. I present estimates and confidence intervals of $\hat{S}_\tau$ in Figure 6, all standard errors are clustered at the physician level. I plot the environmental response for each relative move year.

The migrant's percent change in Medicare acceptance attributable to the change in environment is 45 percent, measured by the average height of the jump in $\hat{S}_\tau$ pre and post migration. This implies that location factors, including aggregate financial incentives, determine about half of a primary care physician's Medicare acceptance policy. Heterogeneity in physician productivity and cost are included in the remaining 55 percent. Results for Medicaid acceptance are similar at the extensive margin, standard errors do not reject equality.

For the extensive margins of Medicare and Medicaid, there is an upward trend in $\hat{S}_\tau$ before migration. There is a weak declining post migration trend. Standard errors reject pre move stationarity at the five, but not one percent level. Stationarity cannot be rejected post move. Pre migration estimates are also negative. This implies acceptance of patients is adaptive. Movers' acceptance of Medicare and Medicaid increasingly mirrors the market environment prior to migration, they move and adjust, and then do not trend differently from non-movers in their destination.

The intensive acceptance margin is less responsive to the broader environment, as mea-

Figure 6: Response of patient acceptance to the market environment



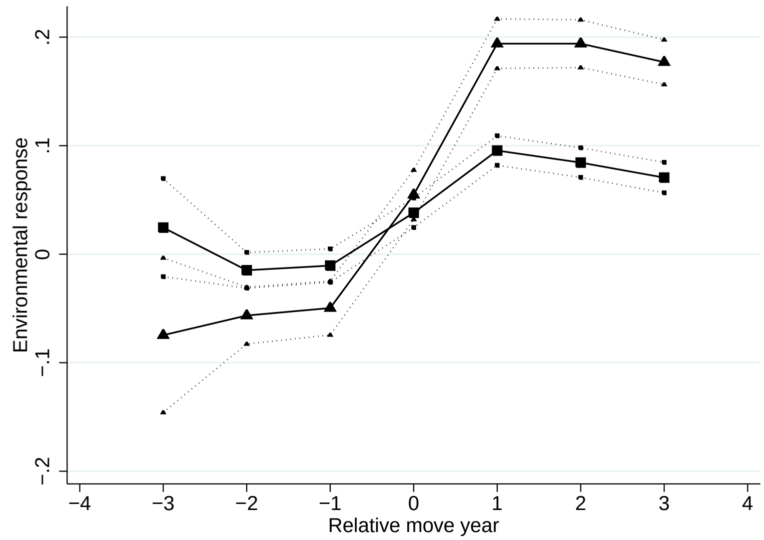
Notes: Estimated percent change ($\hat{S}_\tau$) in Medicare acceptance (circles), Medicaid acceptance (squares), and Medicaid patient fraction (triangles) due to the change in aggregate outcome (δ_j). Dotted lines are $\pm$ 2 std. error confidence intervals. Source: Author's calculations from physician microdata.

sured by the Medicaid patient share conditional on acceptance of Medicare. The estimates $\hat{S}_\tau$ suggest the Medicaid intensive margin trends in parallel with non-movers both before and after a move. The height of the jump between pre and post migration periods is 22 percent. Location factors, including payment regulations, do not determine the majority of the physician's intensive margin acceptance policy. Physician productivity, capacity for patients from private payors, and other idiosyncratic factors are included in the remaining 78 percent.

To further examine the intensive margin, I notice patient disease diagnoses and demographic variables are the most important determinates of the physician's Medicaid acceptance policy. While there are geographic patterns to such factors, results suggest the most salient variation is specific to the physician-patient match. Thus, a mover's reaction to location is a smaller faction of the total response. The responses of accepted-patient's average health risk and of the physician's use of outpatient facilities provide indirect evidence for this. These state variables are thought to be given to the physician by the consumer's health needs and demographics, and thus only controlled through the physician's patient acceptance policy.

Referring to Figure 7, the estimated response of accepted patient health risk to market average health risk is modest. The jump upon migration is eight percent, which indicates that physician acceptance of high risk patients is determined by idiosyncratic factors, and

Figure 7: Response of accepted patient's demographics to the market environment



Notes: Estimated percent change ($\hat{S}_\tau$) in accepted patient health risk (squares) and facility use (triangles) due to the change in aggregate demographic rate (δ_j). Dotted lines are $\pm$ 2 std. error confidence intervals. Source: Author's calculations from physician microdata.

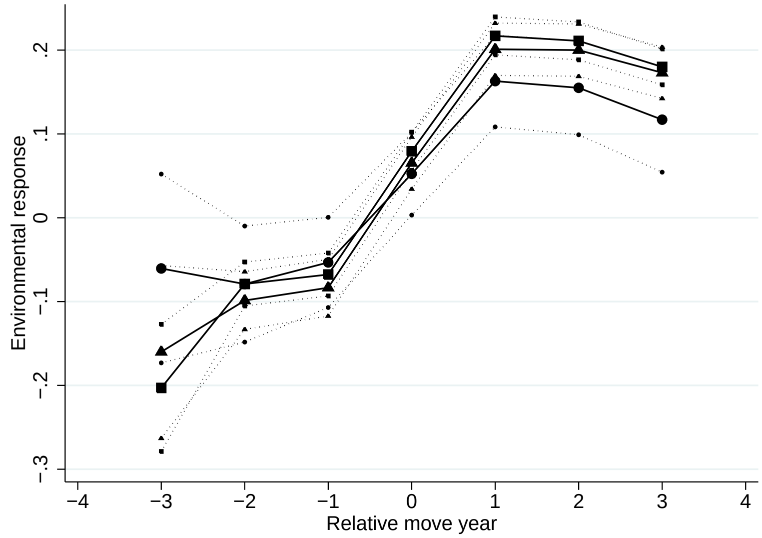
not market average healthiness of elders. In contrast, the facility fraction response to the market environment is 29 percent. This difference is expected: use of an outpatient facility requires spare hospital or other institutional capacity, necessarily a factor of the physician's environment. Standard errors do not reject pre and post move stationarity in $\hat{S}_\tau$ for these outcomes.

4.2.2 Response to environment: practice patterns

Next I analyze the response of physician practice patterns to the market environment. I estimate (2) for the physician's labor to capital ratio, the number of procedures offered, the specialization of the supplied bundle, total capacity for Medicare and Medicaid, and average output per patient. Though the causal effects of financial incentives differed across these outcomes, surprisingly, their responses to broader environmental factors are similar.

In Figure 8, I plot estimates and confidence intervals of $\hat{S}_\tau$ for the labor to capital ratio, the number of procedures, and the bundle specialization measure (HHI). Standard errors do not reject pre and post migration stationarity. However, a weak pre trend is evident in point estimates for the number of procedures offered and for the HHI. The mover's percent change procedures offered due to the change in environment is 32 percent. The jump in the labor to capital ratio is 21 percent. The response of physician specialization is 31 percent. Physician productivity and other idiosyncratic incentives are collected in the remaining 68-79 percent.

Figure 8: Response of practice patterns to the market environment



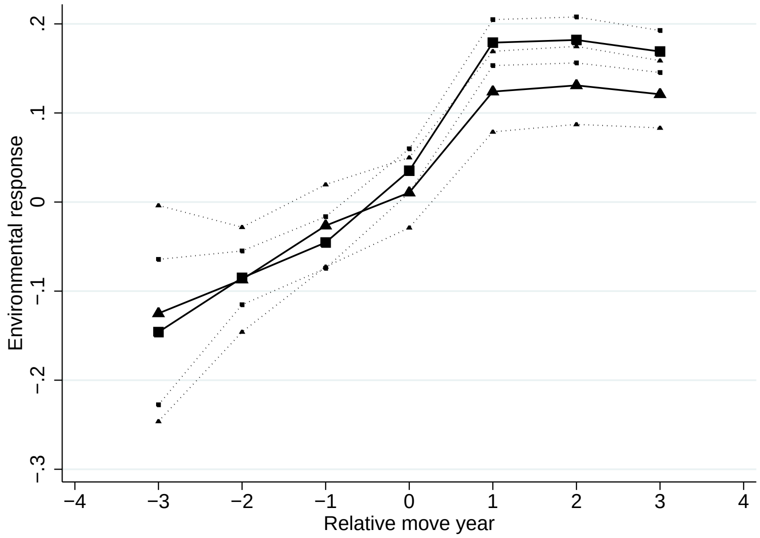
Notes: Estimated percent change ($\hat{S}_\tau$) in labor to capital (circles), number procedures (squares), and specialization HHI (triangles) due to the change in aggregate outcome (δ_j). Dotted lines are ± 2 std. error confidence intervals. Source: Author's calculations from physician microdata.

Market trends affect how accepted patients are treated. However, practice patterns respond less to the market's environment than do the extensive margins of patient acceptance. Moreover, the environmental effect on practice patterns can be similar, while the effects of financial incentives differ. Results for the number of procedures offered versus the physician's degree of specialization illustrates this point. Regulated payments affect total offered procedures, with smaller cost effects. In contrast, payment does not affect the procedural HHI, while cost effects are significant. Yet, equality of the environment responses for these outcomes cannot be rejected statistically, nor rejected visually in Figure 8.

Finally, I examine effects for total Medicare and Medicaid output and for output per patient. These are plotted in Figure 9. The percent change in total capacity attributable to the change in market average capacity upon migration is 26 percent. The jump in output per patient is 21 percent. A pre trend in $\hat{S}_\tau$ is evident, though standard errors do not reject pre move stationarity for either outcome. There is no evidence of physician adaptation post migration.

The physician's output response to changes in the environment is more similar to that of the intensive patient acceptance margin than to other practice patterns. Excepting a small payment effect for sole proprietors, financial incentives had no effect on total output. This supports the opportunity cost of capacity interpretation.

Figure 9: Response of output (RVUs) to the market environment



Notes: Estimated percent change ($\hat{S}_\tau$) in output (squares) and output per patient (triangles) due to the change in aggregate outcome (δ_j). Dotted lines are $\pm$ 2 std. error confidence intervals. Source: Author's calculations from physician microdata.

4.2.3 Summary

Physicians face market factors broader than regulated payment rates and the local prices of production inputs. The overall response to the environment subsumes the effects of aggregate financial incentives. Results from the reduced form models of Section 4.1 show that incentives significantly affect which patients physicians accept. However, the results of Section 4.2 imply environmental factors can only explain 45 percent of the change in extensive margin acceptance following migration, and only 22 percent of the intensive margin. The mover's lemon dropping and cherry picking policy is driven more by idiosyncratic physician-patient factors than by payment regulations.

With respect to practice patterns, I find the response to overarching environmental factors is similar across all outcomes. However, in the results of Section 4.1 payment regulation and local costs were only related to the labor to capital ratio and the number of procedures offered, and plausibly only through a composition effect due to which physicians accept new patients as prices rise. Results are mixed for other outcomes. Moreover, from Section 4.2 the response to environment can only explain 21-32 percent of the practice pattern adjustment. Idiosyncratic factors, including firm specific opportunity costs, are also more important for how physicians treat the patients they accept.

Unlike variation in regulated payments and local factor prices, idiosyncratic financial incentives are not data. However, there are microdata on inputs and output, and market level data on prices. I apply these data in a structural supply model to estimate the idiosyncratic financial incentives that affect practice patterns and patient acceptance.

5 Structural supply model

I examine the idiosyncratic financial incentives of physicians as they determine the fraction of Medicaid patients who are accepted. Structural assumptions on payoffs are needed to define these incentives, and behavioral assumptions on suppliers are needed to estimate them. I take a supply side approach. Throughout, I use notation from the previous sections for individual physicians j, county markets r, and years t.

5.1 Setup: CMS fee-for-service contracts

The model draws from the structure of CMS fee-for-service (FFS) contracts. There are three key features to exploit, and a shortcoming to bring to light. It is unnecessary to distinguish Medicare and Medicaid in this section. These payors will be distinguished later by their output prices.

The first feature of FFS contracts to exploit is additive separability of revenue across physician work output Q_L, practice expense value added Q_K, and malpractice adjustment value added Q_M. The latter captures physician effort abating the risk of medical malpractice liability. FFS revenues are

$$R_{jrt} = p_{Lrt}Q_{Ljt} + p_{Krt}Q_{Kjt} + p_{Mrt}Q_{Mjt}$$

CMS output prices are distinguished across these output categories, and discussed further below.[16] Each value added subcomponent is given in the same "Relative Value Units" (RVUs). The FFS input-output schedule for RVUs does not vary across locations r. Thus, the CMS payment contract is structured as if physicians were a three-product firm, where outputs have common measure and prices have common units.

The unit commonality of outputs, and a set of exclusion restrictions from the input-output schedule, are the second and third advantageous features of FFS contracts I exploit. Let total RVUs supplied be Q_{jrt}. In words, physician labor is excludible from the calculus of practice expense and malpractice value added. Similarly, equipment use is excluded from

[16]These are the CMS "conversion factor" times GPCI indices, which were used to construct the GAF financial incentives measure for the reduced form, see section 2.3 and appendix section 8.2.3.

physician work and effort RVUs. The exclusion restrictions are expressed formally as

$$Q_{jt} = Q_{Ljt}(L_{jt}) + Q_{Kjt}(K_{jt}, \mathbf{S}_{jt}) + Q_{Mjt}(M_{jt})$$

Physician labor L is measured in minutes. Practice expense factors are notated K for medical equipment, and by a vector $\mathbf{S}$ containing the inputs of clinical labor, medical supplies, facility resources, and other overhead. The malpractice risk adjustment Q_{Mjt} measuring physician effort is observed. However, true effort M is unobserved, but is excluded from practice expense and work output value added.

The shortcoming to address is with respect to measurement of factor bills. In the necessary conditions of the model, as in De Loecker, Goldberg, Khandelwal, and Pavcnik (2016), the factor bill to revenue ratio helps identify input-specific opportunity costs. The issue is twofold. First, as true effort is unobserved and there is no market price of effort, measurement of the physician's "effort bill" is difficult. Second, the prices of observed factors are only available in ratios, and denominated in RVUs relative to the input's national mean factor bill. Given the observed price ratios, computing the factor bill to revenue share requires the factor's value-added ratio.[17] Measuring the effort bill additionally requires the use of local malpractice insurance prices.

5.1.1 Primary care production function

The second piece of the model is a structural production function. This function represents the physician's physical production technology for RVU output, subject to the additivity and excludibility conditions of the FFS contract. Knowing the exclusion restrictions and the additive property, I avoid the complications of estimating a joint production function for three-products, and place structure only on a single function for total output $Q : L \times K \times \mathbf{S} \times M \times \mathcal{O} \to RVU \in \mathbb{R}_+$.

I notate the individual physician's total RVU output q_{jrt}. The primary care production technology is

$$q_{jrt} = Q(L_{jt}, K_{jt}, M_{jt}, \mathbf{S}_{jt}, \mathcal{O}_{jrt})$$

The productivity state is $\mathcal{O}_{jrt}$. I assume the productivity state has two components: a scalar factor neutral productivity ω_{jrt}, and a vector of shocks to variable factors $\mathbf{v}_{jrt}$. The latter are health shocks. The former captures effects from unobserved total capacity. Input factors

[17] The bias in this measure is to overstate the factor bill. However, it is the best measure the present data allow. A work in progress is collection of physician average wage data from local hospital wage surveys which contribute to the factor price indices released by CMS. Clinician wages and the medical supplies bill are more exactly measured in the data.

are as defined in the previous subsection.[18] I assume the production function is continuously differentiable, strictly concave in variable inputs (L, K, M), and quasi-concave in intermediate factors $\mathbf{S}$. The timing of $\mathcal{O}$ and physician choices defines the variable/intermediate input distinction, the purpose of which will be clear when estimation is considered.

5.1.2 Prices

I assume physicians are price takers in the output market. This assumption is without loss since prices per RVU are regulated. Let the physician's fraction of capacity chosen for Medicaid be notated l_{jt}. For each input $i \in \{L, K, M\}$ of labor, practice expenses, and effort define the Medicaid output price as p^0_{irt} and the Medicare output price as p^1_{irt}. Define the physician's effective price per RVU given l_{jt} capacity for Medicaid as

$$\bar{p}_{ijrt}(l) := l_{jt}p^0_{irt} + (1 - l_{jt})p^1_{irt}$$

I notate the physician's effective output price vector $\bar{\mathbf{p}}_{rt}(l_{jt})$.

I also assume physicians are price takers in input markets. Input prices are notated $\mathbf{w}_{rt} := (w_{Lrt}, w_{Krt}, w_{Mrt})$. In the data, these are measured by CMS as the market's average factor price. Price taking is a weak assumption for practice expense inputs and effort abating malpractice risk. Medical supplies are commodities sold on a national market. Equipment, too, is supplied on a national market where individual physicians have little monopsony power. Clinicians and administrative staff likely have employment alternatives, even in markets with few physicians. Malpractice insurance prices are set by large insurers.

That physicians are price takers with respect to their own wage is a stronger assumption. Physicians, especially sole proprietors, may be the only demander of their labor. This assumption is necessary without placing additional structure on the labor supply function, requiring knowledge of unobserved capacity for private payor patients. As noted by Becker (1957), monopsony power in wages is one of many microfoundations for the opportunity costs I model next.

5.1.3 Costs

I measure opportunity costs as a percent deviation from market factor prices $\mathbf{w}$. A physician's effective factor price is an opportunity cost parameter times the market price. It is

[18] For capital factors I do observe facility resources and the use of medical equipment. However, I cannot directly measure the true capital stock or total overhead, which includes the physician's human capital, the value of the office building, computers and other office equipment, and the total value of medical equipment on hand. These are small in the RVU calculation. To that extent, they have a negligible marginal revenue product in the FFS contract.

possible that for each factor there are distinct opportunity costs for Medicare and Medicaid patients. For the variable factors of physician labor, effort, and equipment use, I notate these six potential opportunity cost parameters as $(d_L^0, d_L^1, d_M^0, d_M^1, d_K^0, d_K^1)$. For the intermediate inputs of facility resources, clinician labor, and medical supplies, I assume the opportunity costs are common to Medicare and Medicaid. I notate the three intermediate input cost parameters $(d_f, d_{S_{cl}}, d_{S_{ms}})$. Each opportunity cost is a physician-year specific parameter.

As with the effective output price, given the Medicaid capacity share l, the physician's average opportunity cost for variable inputs $i \in \{L, K, M\}$ with heterogeneity is given by

$$\bar{d}_{ijt}(l_{jt}) := l_{jt} d_{ijt}^0 + (1 - l_{jt}) d_{ijt}^1$$

I define the vector of average opportunity costs $\bar{\mathbf{d}}_{jt}(l_{jt})$. For example, the effective cost of labor is $w_{Lrt} \bar{d}_{Ljt}(l_{jt}) L_{jt}$, given l_{jt} Medicaid patients are accepted. The effective cost of equipment is the practice expense $w_{Krt} \bar{d}_{Kjt}(l_{jt}) K_{jt}$.

Given total inputs, the Medicaid fraction, factor prices, and opportunity cost parameters, I model the physician's variable cost function as

$$C(\mathbf{w}_{rt}, \bar{\mathbf{d}}_{jt}(l), L, K, M, \mathbf{S}) = w_{Lrt} \bar{d}_{Ljt}(l) L + w_{Krt} \bar{d}_{Kjt}(l) K + w_{Mrt} \bar{d}_{Mjt}(l) M + (\mathbf{w}_{\mathbf{S}rt} \mathbf{d}_{\mathbf{S}jt}) \cdot \mathbf{S}$$

The data provide measures of average factor bills. The physician-year specific structural parameters $\mathbf{d} := (d_L^0, d_L^1, d_M^0, d_M^1, d_K^0, d_K^1, d_{S_{cl}}, d_{S_{ms}})$ are the idiosyncratic incentives of interest. Unfortunately, the four necessary conditions of optimization, without further assumptions, only identify four of the six possible Medicare-Medicaid heterogeneity parameters for variable cost. I address this in Section 5.2 alongside the first order conditions of optimization.

5.1.4 Payoffs

The third element of the structural model is a payoff function. I assume that physicians value profit. Inserting aforementioned definitions into the FFS revenue equation, payoffs are modeled

$$\pi_{jrt} = R(\mathbf{p}_{rt}(l), L, K, M, \mathbf{S}, \mathcal{O}_{jrt}) - C(\mathbf{w}_{rt}, \mathbf{d}_{jt}(l), L, K, M, \mathbf{S}) - d_{fc}$$

where d_{fc} is the physician's annual fixed cost, which includes the opportunity cost of Medicare and Medicaid participation.

The profit function is stylized in the sense that physicians choose inputs and output separately for Medicare and Medicaid Dual Eligible patients in reality, while in the data only input-output totals and the Medicaid patient fraction are observed. Representing the physician's payoff and choices in the observed variables is restrictive, though without much loss of generality. I assume physicians choose the Medicaid capacity share, labor, equipment, effort, and intermediate inputs taking prices and their production technology as given. Since prices are given and the production technology is continuously differentiable and concave, the payoff function is concave and continuously differentiable in variable factors.

5.2 Necessary conditions from optimization

The final element of the model is a behavioral assumption of profit maximization. The necessary conditions for choices of labor, equipment, effort abating malpractice risk, and the Medicaid capacity share are

$$\bar{p}_{Lrt}(l)\frac{\partial Q}{\partial L} \geq w_{Lrt}\bar{d}_{Ljt}(l)$$
$$\bar{p}_{Krt}(l)\frac{\partial Q}{\partial K} \geq w_{Krt}(1-l_{jt})d^1_{Kjt}$$
$$\bar{p}_{Mrt}(l)\frac{\partial Q}{\partial M} \geq w_{Mrt}(1-l_{jt})d^1_{Mjt}$$
$$(p^0_{rt}-p^1_{rt})Q_{jt} \geq w_{Lrt}L_{jt}(d^0_{Ljt}-d^1_{Ljt}) - w_{Krt}K_{jt}d^1_{Kjt} - w_{Mrt}M_{jt}d^1_{Mjt}$$

where for the sake of identification I have imposed a normalization with respect to the opportunity costs of equipment and effort for Medicaid.

The necessary condition for each intermediate input i is

$$\bar{p}_{Krt}(l)\frac{\partial Q}{\partial S_i} \geq w_{S_irt}d_{S_ijt}$$

where $i \in \{\text{medical supplies}, \text{clinic labor}, \text{facility resources}\}$. In the FFS contract, the output added from intermediate inputs is paid at the same practice expense price, p_K, as equipment. These conditions hold with equality if solutions are interior, which can be observed in the data. Since 87 percent of physicians in the data have interior choices, I estimate the structural model on that subpopulation.

5.2.1 Identification of opportunity costs

The opportunity cost parameters $\bar{\mathbf{d}}$ are identified by variation in factor marginal products between physicians, given the input-output and price data. The marginal products are estimated from the structural production function. Variation in Medicaid capacity then identifies the heterogeneity parameters $(d^0_L, d^1_L, d^0_K, d^1_K, d^0_M, d^1_M)$. Profit maximization only provides four necessary conditions per physician to help identify the six heterogeneity parameters . I consider two approaches to this identification problem.

First, for my preferred estimates I allow heterogeneity in the opportunity cost of physician labor (d_L^0, d_L^1), and normalize with respect to the opportunity costs of equipment and effort for Medicaid patients $d_K^0 = d_M^0 = 0$. The intuition for this normalization is that physicians are most likely to treat Medicaid patients during sub-periods of slack capacity. When total capacity is slack, equipment is already on hand and effort is unconstrained by the needs of other patients, hence the marginal cost of using these inputs is effectively zero.

Second, I maintain heterogeneity in the cost of labor and examine whether the equipment and effort normalizations are sensible. A fifth independent equation is necessary to identify cost heterogeneity across Medicare and Medicaid. For this equation I match a comparative static: the physician's response to an increase in the Medicaid price. The independence of this equation requires (a) a non-zero labor/capital response to the Medicaid price, and (b) an estimate of the response of output capacity.

To derive the fifth condition, let the estimated elasticity of total output be $\hat{E}^Q_{p^0} = \frac{dQ}{dp^0}\frac{p^0}{Q}$, and the estimated elasticity of the labor to capital ratio be $\hat{E}^{L/K}_{p^0} = E^L_{p^0} - E^K_{p^0} = \frac{dL}{dp^0}\frac{p^0}{L} - \frac{dK}{dp^0}\frac{p^0}{K}$. Define the production function's marginal product elasticities as

$$\theta_L := \frac{\partial Q}{\partial L}\frac{L}{Q} \;\;\&\;\; \theta_K := \frac{\partial Q}{\partial K}\frac{K}{Q}$$

With these definitions and the production function, note that

$$E^L_{p^0} = \frac{\hat{E}^Q_{p^0} + \theta_K \hat{E}^{L/K}_{p^0}}{\theta_L + \theta_K} \;\;\&\;\; E^K_{p^0} = \frac{\hat{E}^Q_{p^0} - \theta_L \hat{E}^{L/K}_{p^0}}{\theta_L + \theta_K}$$

Totally differentiating the necessary condition for Medicaid capacity with respect to the Medicaid price, and substituting in the above expressions, I find that

$$p^0_{rt}Q_{jt}(1+\hat{E}^Q_{p^0}) = w_{Lrt}L_{jt}(d^0_{Ljt} - d^1_{Ljt})(\frac{\hat{E}^Q_{p^0} + \theta_{Kjt}\hat{E}^{L/K}_{p^0}}{\theta_{Ljt} + \theta_{Kjt}}) - w_{Krt}K_{jt}d^1_{Kjt}(\frac{\hat{E}^Q_{p^0} - \theta_{Ljt}\hat{E}^{L/K}_{p^0}}{\theta_{Ljt} + \theta_{Kjt}})$$

Given structural estimates of marginal product elasticities $\hat{\theta}_L$ and $\hat{\theta}_K$ and the reduced form estimates $\hat{E}^{L/K}_{p^0}$ and $\hat{E}^Q_{p^0}$, this condition supplies the fifth equation needed to identify (d_M^0, d_M^1) heterogeneity. An analogous derivation provides the equation for identifying (d_K^0, d_K^1) heterogeneity given the normalization $d_M^0 = 0$. Since the reduced form evidence suggests the $(\hat{E}^{L/K}_{p^0}, \hat{E}^Q_{p^0})$ responses may, in fact, be compositional and perhaps even zero, the independence of this equation is suspect.

Nonetheless, I apply this condition and normalize the effort cost to test for Medicare-Medicaid heterogeneity in the cost of equipment, and vice versa. I present these results in the appendix. From this exercise, I find *negative* opportunity costs of effort and equipment for Medicaid patients, which is below the feasible lower bound of zero. This either suggests the preferred normalization is appropriate, or physicians are highly altruistic toward Medicaid.

5.3 Production function estimation

I estimate a semiparametric production function, following Ackerberg, Caves, and Frazer (2015, henceforth ACF) to address simultaneity bias due to unobserved productivity. Productivity has the interpretation of inputs unobserved by the econometrician, but which nevertheless add to RVUs and are in inelastic supply. In the present setting, a literal translation is unobserved overhead, and unseen shocks to patient health requiring unobserved variation in labor, effort, or equipment use. The approach is to assume a data generating process with judicious timing of productivity shocks and primary care input choices.

To present the formal assumptions, define log output as $\tilde{q}$ and log inputs $(\tilde{L}, \tilde{K}, \tilde{M}, \tilde{\mathbf{S}})$. I assume a production function of the form

$$(3) \qquad \tilde{q}_{jrt} = f(\tilde{L}_{jt}, \tilde{K}_{jt}, \tilde{M}_{jt}, \tilde{\mathbf{S}}_{jt}, \mathbf{v}_{jrt}) + \omega_{jrt} + \epsilon_{jrt}$$

where ω is factor neutral productivity and $\mathbf{v}$ is a vector of patient health shocks, one for each variable factor. The function $f()$ is estimated as a second order complete polynomial sieve with 22 parameters, and the residual ϵ is orthogonal error. Clearly, the physician's choice of inputs will depend on knowledge of productivity, and more generally on a set of available information. I now turn to ACF for two procedures which address identification.

5.3.1 Identification without health shocks

Define the physician's information set at time t as I_{jt}. I assume at least one intermediate input of $\mathbf{S}_{jt}$, say facility resources S_f, is a perfect complement in production. This "value added" framework implies that facility resources are excluded from physician's RVU production function. The facility example is deliberate, since in the FFS contract physicians are not compensated for their use facility resources when performing services in that setting, hence using more (or less) of these inputs does not affect their production of RVUs. A similar argument can be applied to medical supplies. A procedure requiring a pair of rubber gloves produces no more RVUs if three rubber gloves are used instead.

I assume intermediate input demand is a vector valued function where each element is strictly increasing in the scalar productivity ω.

$$(A1) \qquad \mathbf{S}_{jt} = \mathbf{D}(L_{jt}, K_{jt}, M_{jt}, \omega_{jrt})$$

I further assume factor neutral productivity evolves by a first order markov process

$$(A2) \quad \omega_{jrt} = g(\omega_{jrt-1}) + \xi_{jrt}$$

where the function $g()$ is a conditional expectation $\mathbb{E}(\omega_{jrt}|\omega_{jrt-1})$ and the innovation ξ_{jrt} is iid. I assume the error is strictly exogenous given the present information set

$$(A3) \qquad \mathbb{E}(\epsilon_{jrt}|I_{jrt}) = 0$$

I assume innovations ξ are unknown in the previous period

$$(A4) \qquad \mathbb{E}(\xi_{jrt} + \epsilon_{jrt}|I_{jrt-1}) = 0$$

The ACF argument for identification of (3) given these assumptions is as follows. Input demands (L, K, M) depend on productivity, so the function $f()$ is not identified separately from ω. However, (A3) separates production $f() + \omega$ from error ϵ. Since intermediate inputs are monotone in ω, the functions $D()$ are invertible. At least one of these inputs is excludible from $f()$. Together with (A2), excludibility and (A4) provides moment conditions to identify the parameters of $f()$ and $g()$.

5.3.2 Identification with health shocks

ACF show that (A1)-(A3) is sufficient to estimate the variable factor parameters of $f()$ if there are shocks $\mathbf{v}_{jrt}$ to variable factor productivity that are independent of ξ, and that are learned after intermediate inputs are chosen by the physician. This assumption "saves" the first stage of Levinsohn and Petrin (2003, henceforth LP). Shocks to patient health are an intuitive microfoundation for $\mathbf{v}_{jrt}$. For (A1)-(A3) to be sufficient to estimate the marginal products of labor, equipment use, and effort, (L, K, M), physicians must choose their facility policy, clinical staff, and/or store room of supplies prior to learning their patient's present health state. After observing the patient's health, the physician then chooses labor, which equipment on hand to use, and how much effort is required to address those needs.

While ACF argue this latter data generating process is a very special case, it is plausible in the present setting. There is evidence in the data supporting this assumption. Referring to Figure 3, in Section 3.3, the physician's observed average patient health varies widely from year to year. Unobserved patient health is likely also volatile.

Moreover, the exclusion restrictions inherent to the FFS contract input-output schedule provide evidence for ACF's required Leontief type complementarity. This is certainly true in the case of services in a facility setting, where physicians are not reimbursed for their use of additional facility resources. The strong complementarity condition also likely applies both for medical supplies already stocked and clinicians already employed by the physician. Only one syringe is needed to draw a patient's blood, and the physician does not produce extra RVUs if two syringes are used instead.

I examine estimates of the production function under both scenarios. I also consider a hybrid of LP employing physician fixed effects, motivated by the panel dimensions of the data, the unobservability of physician human capital with the presence of effort in the production function, and the unobservability of the physician's private payor capacity. The straight ACF method of moments estimator is presently a work in progress. For the remainder of this paper, I present results from the LP estimators. The LP estimator with physician fixed effects are the preferred estimates.[19]

5.4 Structural model results

In this section, I report the estimated parameters of the primary care production function and the opportunity cost estimates identified from variation in marginal products. I denote the marginal product elasticity of labor, $\hat{\theta}_{Ljt}$, of equipment $\hat{\theta}_{Kjt}$, and of effort $\hat{\theta}_{Mjt}$. I present the estimated means of these structural parameters in Table 12. I treat facility resources as the complementary (Leontief) intermediate input.

The standard errors indicate precise estimates at the mean, significant to three or more digits. The estimated marginal products of labor and effort are not very sensitive to the estimation method. Labor is smaller in the standard LP estimator, swapping rolls with effort. However, the labor product is sensitive to the exclusion of effort from the production function. When effort is excluded, the labor elasticity nearly doubles in size across the distribution, combining the underlying products of effort and labor. This is evidence supporting the interpretation of the malpractice risk adjustment as physician effort.

The marginal products of equipment and clinician labor are more sensitive to the estimation method. In the baseline LP estimator, Column 2 in Table 12, the mean equipment elasticity is 0.07. While the overall insignificance of this factor is unchanged, moving from the standard LP technique to one augmented with physician fixed effects decreases the estimated mean by 28 percent. Most of the change happens in clinician labor, where the baseline LP estimate provides an mean elasticity of 0.14. Adding fixed effects to this approach reduces the mean by 64 percent, and redistributes the marginal contribution of clinician labor primarily toward physician labor and effort.

[19] A drawback of the fixed effects estimator is it can attenuate the coefficients on capital inputs. I find little evidence of this. I find the estimated marginal products are not very sensitive to the estimation method.

Table 12: LP estimated structural parameters

Physician labor $\hat{\theta}_L$	0.403	0.329	0.462
	(0.003)	(0.003)	(0.003)
Equipment $\hat{\theta}_K$	0.086	0.067	0.050
	(0.001)	(0.001)	(0.001)
Effort $\hat{\theta}_M$	0.409	0.440	0.407
	(0.003)	(0.003)	(0.004)
Clinic labor $\hat{\theta}_{S_{cl}}$	0.064	0.138	0.053
	(0.001)	(0.001)	(0.001)
Supplies $\hat{\theta}_{S_{ms}}$	0.041	0.035	0.025
	(0.00)	(0.000)	(0.000)
Patient controls	X	X	X
Nonlinear $Q(\cdot)$		X	X
Physician FE			X

Notes: Observations: 864,323. Author's calculations from physician microdata using subsample of physicians with interior inputs. Levinsohn and Petrin (2003) estimation method, assuming health shocks are timed as in Ackerberg, Caves, and Frazer (2005). Delta method standard errors clustered by physician in parenthesis. Controls are for patient demographics and health.

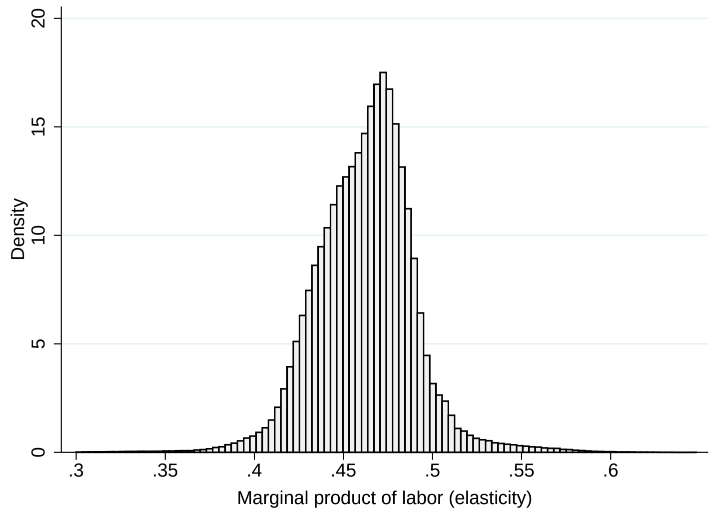
5.4.1 Estimated marginal product heterogeneity

Labor is the most important factor in the primary care production function. I find that the marginal product of labor varies across physicians. The density of the estimated marginal product elasticities $\hat{\theta}_{Ljt}$ is plotted in Figure 10. The average and median elasticities of labor are near 0.46. The distribution has minor skew, with support over [0.19,0.68]. I find the distribution of labor marginal products is similar whether the primary care physician supplies in an office or a in facility setting.

The effort marginal product elasticity has a similar, though dominated, distribution to labor. I plot the estimated distribution of $\hat{\theta}_{Mjt}$ across office/facility settings in Figure 11. The mean and median effort elasticities are near 0.41. Unlike labor minutes, I find that the marginal product of effort abating medical malpractice risk falls with facility use. Physicians are jointly rather than solely liable in the facility setting, their effort is less important for financial risk.

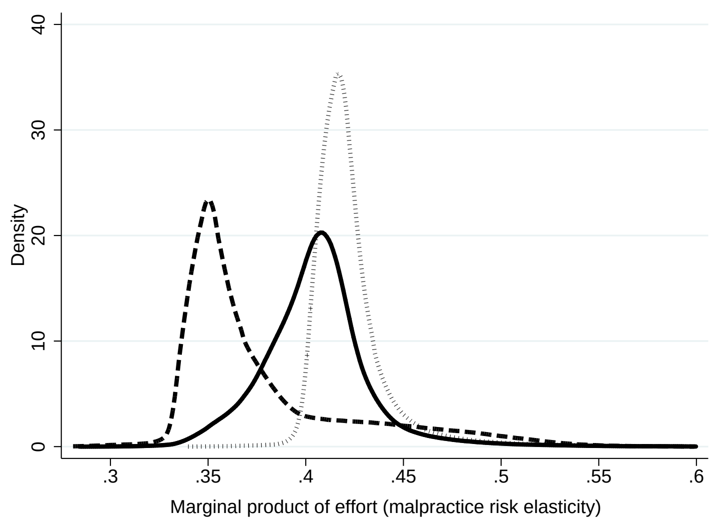
The estimated marginal products of equipment capital $\hat{\theta}_{Kjt}$, clinical labor $\hat{\theta}_{S_{cl}jt}$, and medical supplies $\hat{\theta}_{S_{ms}jt}$ are small compared to the products of physician labor and effort in primary care. However, there is dispersion in their marginal contributions across suppliers.

Figure 10: Empirical distribution of marginal product elasticity of physician labor $\hat{\theta}_{Ljt}$



Notes: Histogram of estimated RVU marginal product elasticity of labor $\frac{\partial Q}{\partial L}\frac{L}{Q}$ from the structural production function. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

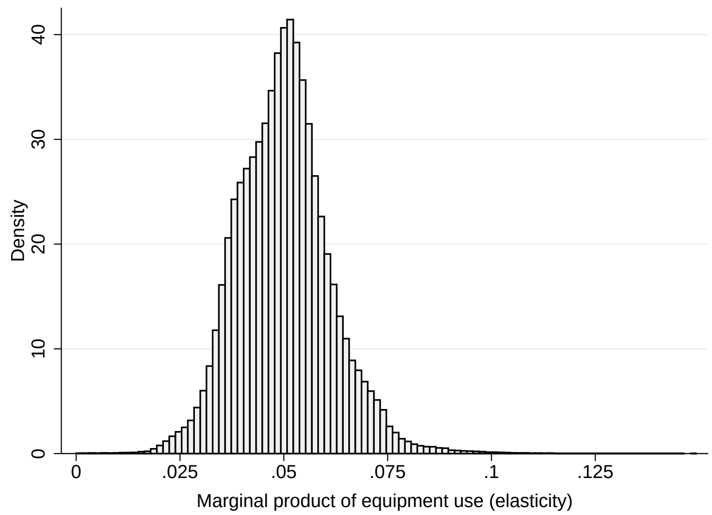
Figure 11: Empirical distribution of marginal product elasticity of physician effort $\hat{\theta}_{Mjt}$



Notes: Office setting (dashed, left) versus facility setting (dotted, right) versus mixed facility/office (bold, center) kernel density estimated RVU marginal product elasticity of effort $\frac{\partial Q}{\partial M}\frac{M}{Q}$ from the structural production function. A rectangular kernel function was used. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs,observations 864,323.

I plot the empirical density of the marginal product elasticity of equipment in Figure 12. The mean and median of the distribution is near 0.05, an order of magnitude below labor and effort. The mean and median of the estimated clinician labor elasticity is also 0.05; for medical supplies, like rubber gloves, the mean and median are near 0.02.

Figure 12: Empirical distribution of marginal product elasticity of equipment use $\hat{\theta}_{Kjt}$



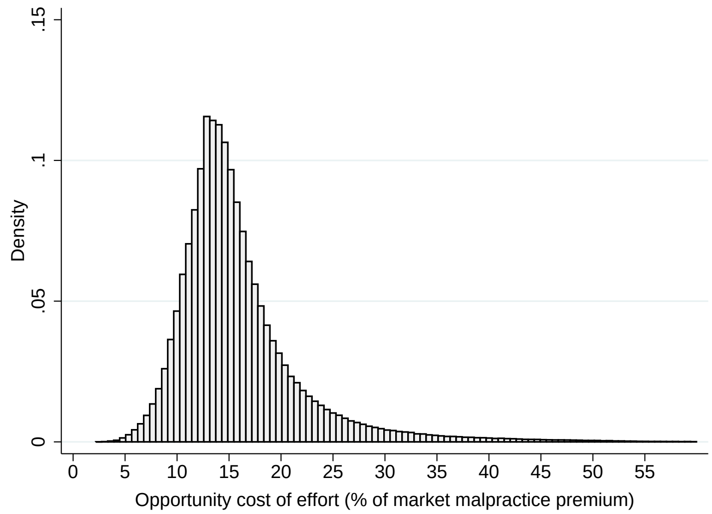
Notes: Histogram of estimated RVU marginal product elasticity of equipment capital $\frac{\partial Q}{\partial K}\frac{K}{Q}$ from the structural production function. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

5.4.2 Estimated opportunity cost heterogeneity

The necessary conditions for an interior optimum profit relate variation in the physician marginal product of labor to variation in the physician's average opportunity costs of labor $\hat{\bar{d}}_{Ljt}(l_{jt})$, given the Medicaid capacity share l. The average is identified by the estimated marginal product and price ratio data. Together with the necessary condition for the capacity share, this in turn identifies the decomposition of cost across Medicare and Medicaid Dual Eligibles $(\hat{d}^0_{Ljt}, \hat{d}^1_{Ljt})$. For equipment and effort inputs, only the first order conditions are required since I have normalized the opportunity costs of Medicaid.[20]

[20] Each market's output/input price ratio and the physician's Medicaid share are data. However, the price ratios are given in output units. As a result, in the necessary conditions the estimated marginal product elasticity must be scaled by the input's observed valued added share to obtain the level of the marginal product. This allows use of the reported factor bill, which is only provided in the data in units of output added. For example, Q/Q_L scales the labor marginal product elasticity. For labor and effort these output shares are well measured in the FFS contract data. For equipment, the value added share is not directly measured, and must be imputed from the broader value of all practice expenses. I draw from two industry white papers to perform this imputation, Pope and Burge (1993) and Mackinney et al (2003). Each paper finds that "direct practice expenses" account for 33-35 percent of the total practice expense, putting an upper bound on the equipment bill. For a subset of physicians in the data I observe the share of equipment expenses to direct practice expenses, and I use their average share times 1/3 times the total practice expense bill to impute equipment value added.

Figure 13: Heterogeneity in the opportunity cost of physician effort



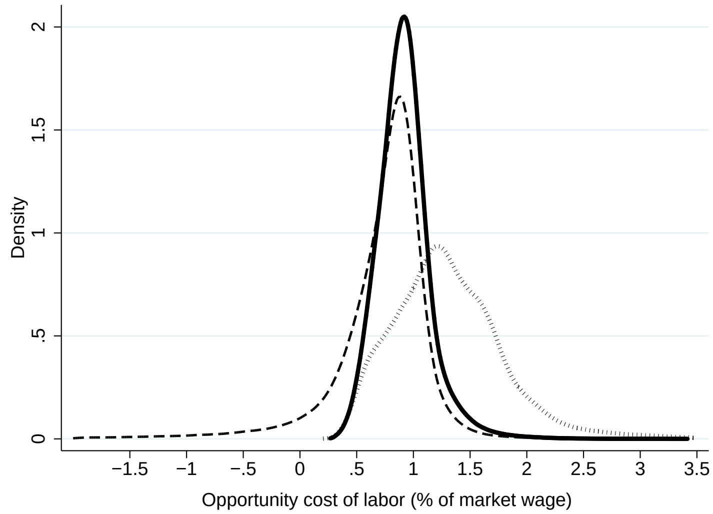
Notes: Histogram of estimated heterogeneity in the opportunity cost of physician effort for Medicare $\hat{d}^1_M$ patients. The opportunity cost of Medicaid effort is normalized $\hat{d}^0_M = 0$. Opportunity cost is measured as a percent deviation from the county average medical practice insurance premium. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

I find that the opportunity cost of effort abating malpractice risk is greatest. In Figure 13, I plot the density of estimated heterogeneity across physicians in this cost, measured relative to the market malpractice insurance price. The results indicate that the average opportunity cost of effort is 16 times the insurance premium. Measuring in reference to insurance prices is the best that can be done, but is nonetheless opaque.

A different metric is available by conversion of the implied cost into output units using the measured factor bill and price index. In output units, the mean effective cost of effort is worth 2,051 RVUs, and is worth 1,163 RVUs at the median. By comparison, in the FFS payment contract only 138 RVUs are the average product of malpractice risk adjustments. This suggest physicians view the effective cost of effort avoiding malpractice liability as greater than the effective cost of labor.

I plot the empirical distributions of estimated labor cost heterogeneity in Figure 15. This cost is measured relative to the market average wage. The median and mean of physician expected opportunity cost of labor, given the Medicaid capacity share, are 91 and 93 percent of the market wage, respectively. The distribution of Medicare opportunity cost is dominated by the Medicaid distribution. The estimates imply the physician's opportunity cost of labor for Medicaid patients is high, the average being 32 percent above the market price. This result is unsurprising, given the low regulated price of Medicaid. Denominating this cost

Figure 14: Heterogeneity in the opportunity cost of physician labor



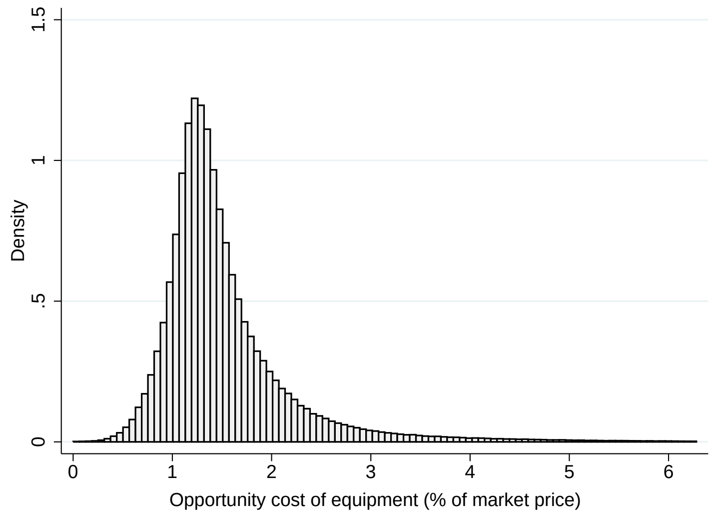
Notes: Kernel density of estimated heterogeneity in the opportunity cost of physician labor for Medicare $\hat{d}_L^1$ (dashed, left), Medicaid $\hat{d}_L^0$ (dotted, right), and the physician's average $\hat{\bar{d}}_L$ (bold, center), measured as a percent deviation from the county wage. A rectangular kernel with bandwidth 0.1 was used. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

in output units, I find the mean effective cost of labor is worth 1,649 RVUs, and that the median is worth 1,097 RVUs. In contrast to effort, in the FFS payment contract physician labor produces 1,847 RVUs at the mean. This suggests the effective cost of labor is well compensated by Medicare, while the cost of effort is mostly uncompensated.

In Figure 15, I plot the empirical density of the physician's opportunity cost of equipment for Medicare. This cost parameter is measured relative to the market's average practice expense. This price is the metric by which equipment use is reimbursed in the FFS contract, and is a weighted average of all practice expense inputs including but not lmited to equipment. I find that the opportunity cost of equipment is greater than the opportunity cost of physician labor, relative to the market price. The average opportunity cost of equipment is 60 percent above the market rate, the median 36 percent above the market.

However, I find wide dispersion across physicians in the cost of equipment, and that the effective equipment bill is small. In the distribution of opportunity costs, 13 percent of physicians face equipment prices below the market practice expense. Denominating this cost in output units, I find that the average effective equipment bill is worth only 235 RVUs, and that the median is worth 152. In the FFS contract, equipment produces 181 billable RVUs on average and 106 billable RVUs at the median. This suggests that, even accounting for the large opportunity cost relative to the market, equipment is not comparable to the effective

Figure 15: Heterogeneity in the opportunity cost of equipment



Notes: Histogram of estimated heterogeneity in the opportunity cost of equipment use for Medicare patients $\hat{d}_K^1$. The Medicaid cost is normalized, $d_K^0 = 0$. Opportunity cost is measured as a percent deviation from the mean county practice expense. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

costs of physician labor and effort in primary care.

In the appendix, I provide robustness results for the decomposition of the opportunity costs of equipment and effort across Medicare and Medicaid without the employed normalization. I find that the estimated opportunity costs of equipment and effort for Medicaid are negative, and are large and positive for Medicare. The negative cost is below feasible economic lower bound on marginal cost.

The results of the robustness exercise are interpretable as Medicaid patients having zero marginal cost of equipment use and physician effort. Otherwise, the results indicate significant physician altruism for Medicaid patients. One interpretation for a zero marginal cost of capital is if Medicaid patients are being serviced during periods of slack capacity.

5.4.3 Summary

The products of physician labor and effort are most important in primary care. From the estimated production function, there is dispersion across physicians in the marginal product of each of these factors. The product of equipment, and intermediate factors like clinician labor or medical supplies, are an order of magnitude smaller than those of labor and effort. However, these factors too have dispersed marginal contributions across physicians.

The opportunity cost of physician labor varies across Medicare and Medicaid patients.

Medicaid imposes a higher opportunity cost on physician time. However, the evidence suggests the opportunity costs of effort and equipment are at the zero lower bound for Medicaid patients. This is interpretable as Medicaid receiving care from physicians during sub-periods of slack capacity. If equipment is on hand and there are few other patients in the office demanding effort, the marginal cost of these inputs is effectively zero.

The opportunity costs of effort and equipment for Medicare, however, are most important. The effective cost of effort abating medical malpractice risk is high enough to at least equal the physician's effective wage bill. While the opportunity cost of equipment is high relative to the market price, I find that the effective equipment bill is small compared to the labor and effort factor bills. Dispersion in estimated opportunity costs suggests wide dispersion in physician average costs. I now use the structural estimates to predict the physician's average variable cost and average variable profit.

6 Price and profit counterfactuals

6.1 Estimated lower bounds on average variable profit

The necessary conditions of profit maximization, together with output and price data, provide a lower bound on average variable profit. Returning to the profit model and the FFS contract revenue equation in Section 5.1, I find the implied lower bound of variable profit is

$$\bar{\pi}^{lb}_{jrt} = \bar{p}_{Lrt}(l_{jt})(\frac{Q_{Ljt}}{Q_{jt}} - \hat{\theta}_{Ljt}) + \bar{p}_{Krt}(l_{jt})(\frac{Q_{Kjt}}{Q_{jt}} - \hat{\theta}_{Kjt}) + \bar{p}_{Mrt}(l_{jt})(\frac{Q_{Mjt}}{Q_{jt}} - \hat{\theta}_{Mjt})$$

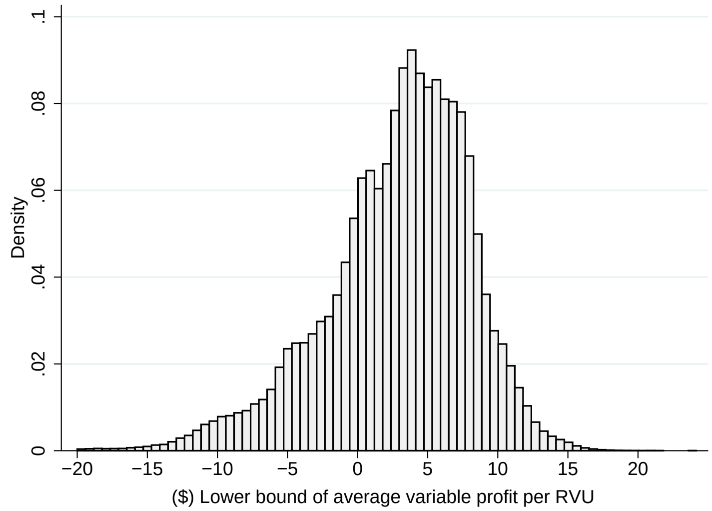
I estimate this equation for each physician each year and plot the distribution of estimated profit in Figure 16.

The estimates plotted in Figure 16 illustrate that 76 percent of primary care physicians have a positive lower bound on variable profit. To provide context for these estimates, the national average Medicare price per RVU ranged from \$34.02-\$35.82 over 2012-2015. This implies a lower bound average markup of ten percent at the median, and eight percent at the mean. However, in the right tail of the estimated profit distribution the markup is only 43 percent, and many physicians have a lower bound markup estimated below zero.

6.2 Competitive prices

I consider two free market counterfactuals to the present regulated price environment. I first use the structural model to estimate physician-year specific average variable costs per output unit (RVU) supplied. This is the predicted short run distribution of prices should the

Figure 16: Empirical density of estimated lower bound of average variable profit



Notes: Histogram of estimated physician-year heterogeneity in average variable profit per Relative Value Unit (RVU). Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

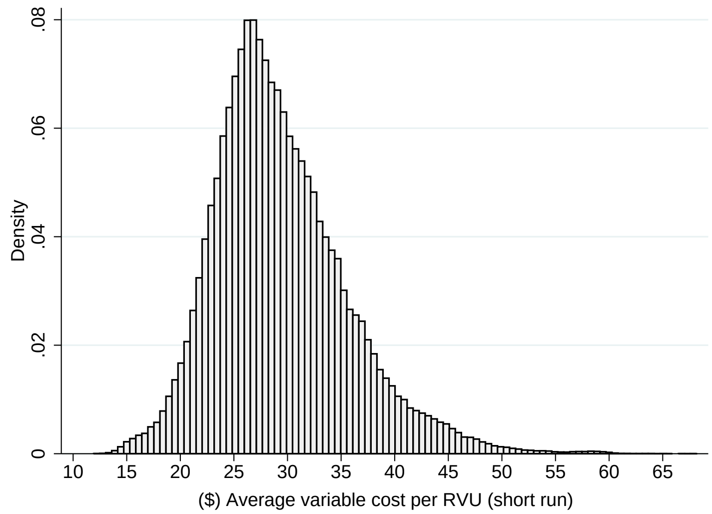
primary care industry be monopolistically competitive. The second counterfactual considers a more plausible industry structure, the scenario perfect competition with inframarginal firms.

6.2.1 Short run AVC: monopolistically competitive prices

I plot the empirical density of estimated average variable cost in Figure 17. I find that monopolistically competitive prices are largely within the support of observed regulated prices. Average variable costs per RVU are widely dispersed. The dispersion is not only across locations, but across physicians within a location. The latter is driven in the model by variation in the marginal products of physician labor and effort. I interpret this as due to the physician's total capacity constraint, including capacity allocated to private payor patients.

The average price under monopolistic competition is $29.32 per RVU, a reduction of 16.2 percent from the regulated price. The entry threshold regressions, Table 3 in Section 3.2, found a Medicare acceptance own price elasticity of 1.31. This suggests the price change would cause average Medicare acceptance rates to *fall* from 71 percent to 56 percent, holding market size constant. Competition in this scenario is not welfare improving for patients.

Figure 17: Empirical density of estimated average variable cost



Notes: Histogram of estimated physician-year heterogeneity in average variable cost per Relative Value Unit (RVU). Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs, observations 864,323.

6.2.2 Perfectly competitive prices with inframarginal firms

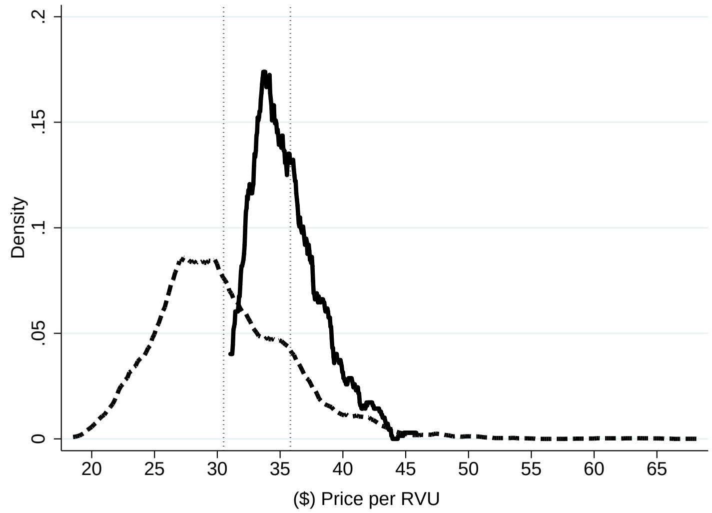
Next I consider the model of a homogeneous product industry with inframarginal firms. In this setting, the equilibrium price is the average variable cost of the marginal firm in each county each year. To compute counterfactual short run competitive equilibrium prices, I take the empirical maximum average variable cost from the structural model, market by market. I plot the distribution of these prices across counties, alongside the prevailing regulated prices, in Figure 18.

The perfectly competitive price counterfactual differs from the monopolistically competitive counterfactual in two important ways. First, the average price across markets falls to \$30.5 per RVU, a reduction of only 12.8 percent from the average of regulated prices. Second, there is a long thin upper tail of the distribution which *raises* prices relative to regulation.

The price reduction together with the results of the entry threshold regressions, which control for market size, suggest the perfectly competitive equilibrium would reduce Medicare acceptance on average from 71 percent to 59 percent. This reduction in access is bad for consumer welfare. However, consumers are better off under perfect competition than under monopolistic competition.

The effect on total welfare is ambiguous. While these results imply consumers are hurt by competition, some physicians in the industry are better off in the perfectly competitive scenario. The distribution of counterfactual average variable profits is strictly positive. In

Figure 18: Empirical densities of current prices and estimated short run competitve prices



Notes: Kernell density estimates of counterfactual price per Relative Value Unit (RVU) under short run competition with inframarginal firms (dashed, left), and current Medicare prices (solid, right). A rectangular kernel was used with a bandwidth of $1 per RVU. Reference lines are for the average competitive price, and the average actual Medicare price in 2015, respectively. Source: Author's calculations from county aggregates of physician microdata panel.

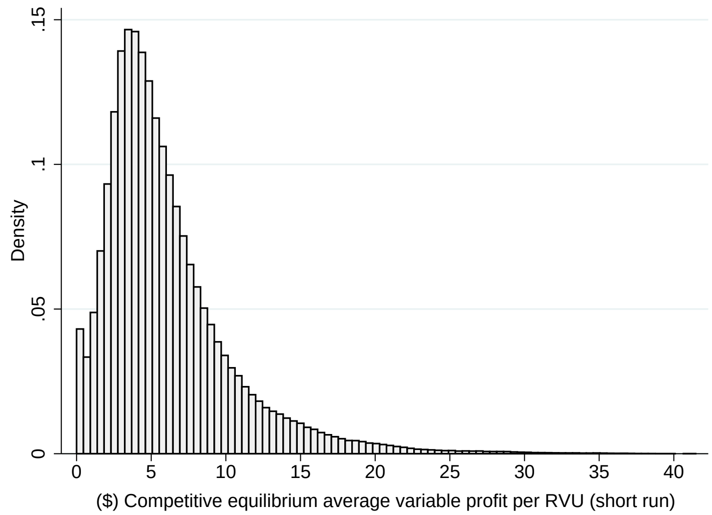
contrast, the estimated average variable profit under regulation was negative for 24 percent of firms. The difference is driven by markets in the tail, where prices increase. I plot the counterfactual competitive profit distribution in Figure 19. The point mass at zero are the estimated marginal firms. The density of positive profits are driven by inframarginal cost heterogeneity.

6.3 Equal Medicare and Medicaid prices

Leaving the Medicare price unchanged, I last consider the effect of increasing the Medicaid price equal to Medicare's across locations. I plot the estimated percent increase in Medicaid prices in Figure 20. I compute the counterfactual increase in acceptance along the Medicaid extensive margin, again using the entry threshold regressions for initial guidance. The Medicaid elasticty in those regression results was either zero or 0.37, an inelastic response.

The mean percent increase in Medicaid payment is 38 percent. The estimated acceptance response, controlling for market size, implies the average Medicaid acceptance rate would increase by 14 percent. At the mean, these results imply counterfactual Medicaid acceptance would rise from 62 percent to 70.7 percent under equal payments. This is nearly the observed acceptance rate of Medicare, at 71 percent.

Figure 19: Empirical density of average variable profit in competitive equilibrium



Notes: Histogram of estimated physician-year heterogeneity in average variable profit per Relative Value Unit (RVU), assuming short run competitive equilibrium with inframarginal firms. Source: Author's calculations from physician microdata panel, from the subpopulation with interior inputs.

The results from the microdata regressions in Section 4.1.1 predict a very similar counterfactual acceptance effect. Discussed in the reduced form section, physicians at the Medicaid extensive margin are induced by equal payment to acceptance patients at their county's Medicaid-Medicare population share. These two counterfactual approaches suggest that equating Medicare and Medicaid payments would erase the primary care access gap for Medicaid. Other results are TBD.[21]

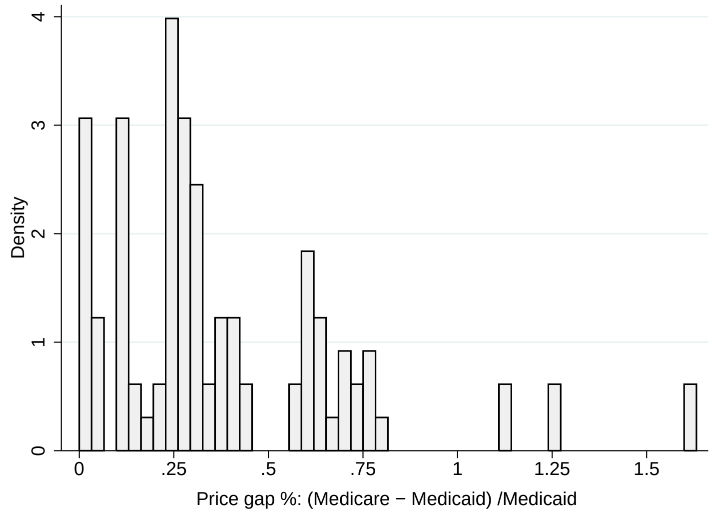
7 Conclusion

Physicians have financial incentives to accept high payment patients, especially when capacity is scarce. The generosity of private payors ensures those patients are prioritized, leaving less room for Medicare and Medicaid Dual Eligible patients in a physician's day. Do physicians accept or reject these patients based on their ability to pay? The terms "lemon dropping" and "cherry picking" have entered industry colloquial, suggesting financial incentives are most salient at the formation of the physician-patient relationship. Indeed, I find that lemon dropping is the effect of incentives at the patient acceptance margin.

I find little evidence that financial incentives affect practice patterns in a nefarious way. Though payment and cost are associated with changes in practice patterns, the effects can

[21] Please see my website for the latest version of this paper, https://sites.northwestern.edu/dab204/

Figure 20: Percent price increase closing the Medicare-Medicaid payment gap



Notes: Histogram of the countferfactual percent increase in Medicaid prices required to erase the Medicare-Medicaid payment wedge. Source: Author's calculations from county financial incentives panel.

be interpreted entirely as physician heterogeneity acting through an extensive margin of acceptance. Seemingly, primary care physicians first do no harm. However, they are capacity constrained, and allocate capacity favorably to private payor patients. Medicare receives capacity next. I find that the Medicaid patient, who pays the physician the lowest price of all, is most often the lemon without access to care.

The empirical results show that physician heterogeneity in cost is the paramount incentive at acceptance. Payment closely follows. The structural results confirm that Medicaid patients impose a high opportunity cost of physician labor. This cost adds insult to already low payment rates offered by the regulator for these patients. Medicare is unattractive compared to private payors, to the extent that these patients first have a high opportunity cost of physician effort, and secondly a high opportunity cost of equipment use.

This study is an exercise in the unintended consequences of price regulation in a competitive industry. The counterfactual analysis suggests that allowing the free market and competition to set prices would be worse than regulation for Medicare and Medicaid consumers, while perhaps better for some physicians. In the regulatory counterfactual, the results imply that the Medicaid access gap would be erased if payment for treating these patients were equal to that of Medicare. A remedy for lemon dropping may be as simple as giving Medicaid price setting authority to the federal government, away from the hands of the states, and equating physician payments across these two important public insurance programs.

8 Appendix

Parts of the appendix are TBD.[22]

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[22] Please see my website for the latest version of this paper, https://sites.northwestern.edu/dab204/

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8.2 Data and measurement

8.2.1 Details on sources and patient acceptance

The physician microdata panel was constructed from two sources. Physician identities, locations, and demographic data were obtained from monthly publications of the the National Plan and Provider Enumeration System (NPPES) over 2011-2017.[23] The data contain a unique National Provider Identifier (NPI) number for all covered healthcare providers, including the population of physicians. Each provider in the NPPES is further classified by

[23]Thanks to the NBER for making historical records of these data available. The NPPES is an administrative database created in 2007 by the Centers for Medicare and Medicaid Services (CMS) to fulfill mandates of the Health Insurance Portability and Accountability Act of 1996 (HIPAA).

CMS's Healthcare Provider Taxonomy Code Set. NPI numbers with taxonomy codes for Internal Medicine, Family Practice, and General Practice physicians were extracted as the primary care subpopulation. Location is taken as the postal address of the physician's primary medical practice, which includes zip code.[24]

The source of outcomes and market data are 2012-2015 annual Medicare Physician and Other Supplier Public Use Files, also published by CMS. These data contain 100 percent of final-action Medicare Part B non-institutional line items billed for the Medicare fee-for-service population. Medicare Part B covers medically necessary services supplied in a physician's office or outpatient facility setting. These data were linked to the NPPES by NPI and year. As both sources are population data, successful merger measures Medicare acceptance.

The outcomes data come in two forms. First is physician-year level data. These files include total Medicare Part B revenue, counts for billed line items[25], total procedures offered, average patient demographics and disease diagnoses, and unique consumer counts for the Medicare and Medicaid Dual Eligible populations. A second file includes billing data at the physician-procedure-setting level. "Setting" is defined as the physician's office or an outpatient facility, payment regulations vary across setting. The physician's procedural bundle is used to measure practice patterns, detailed in the next subsection. These data are subject to mild censoring: procedures billed to 10 or fewer consumers are omitted for privacy concerns.

Outcomes data for the entire population are available only for the physician's Medicare Part B and Medicaid Dual Eligible business. For a small representative subsample of the population, the National Ambulatory Medical Care Survey (NAMCS) is available over 2011-2014. These data provide measures for the physician's total business, and directly survey physician patient acceptance policies. However, they are a repeated cross-section, and lack detailed location data or identifiers necessary to merge with the physician microdata. I use these data for one purpose: to measure the Medicare and Medicaid shares of the physician's business.

8.2.2 Details on practice patterns

I examine five measures of physician practice patterns. Two measures with important economic content, total output and the labor to capital ratio, must be constructed by merging the physician bundle data with input-output metrics observed in the CMS payment con-

[24] Other geographic boundaries were merged by zip code crosswalks: county, state, Medicare Locality, and Dartmouth Atlas Hospital Service Areas (HSAs) and Hospital Referral Regions (HRRs), the latter useed for robustness exercises.

[25] Line items are healthcare procedures demarcated by CMS using the Healthcare Common Procedural Coding System (HCPCS) and American Medical Association Current Procedural Terminology (CPT) codes.

tract. The CMS fee-for-service (FFS) contract is built around a healthcare output metric of Relative Value Units (RVUs). The universe of medical procedures are distinguished by Current Procedural Terminology (CPT) codes. The FFS contract assigns each CPT code an RVU for physician labor, for practice expenses, and for medical malpractice risk adjustment. Payment for service is a fixed price per RVU supplied in each category.

To construct RVUs, CMS and the American Medical Association solicit production inputs and costs from a representative survey of physicians. For each procedure, they survey physician labor minutes supplied, medical equipment and supplies used, and the labor of assistants including nurses, technicians, and other staff. Also surveyed are overhead expenses like the physician's office rent, administrative wage bills, and expenses for outsourced professional services. Estimates of production inputs and the assigned RVU output index are published annually at the procedure (CPT) level by CMS in their Relative Value Files.

I merge these input-output data with the physician bundle data by procedure and year.[26] To measure total output, I compute total RVUs supplied by summing over uncensored billed procedures. I likewise compute total labor minutes supplied, total equipment supplied, total medical supplies used, and total assistant labor minutes from the bundle data. I measure the labor to capital ratio as physician labor minutes per use of equipment.

Standard practice in the literature is to measure output with deflated revenues, termed "healthcare utilization." For example, Gottlieb et al (2010) and Finkelstein, Gentzkow, and Williams (2016) strip revenues of regulated prices with a regression procedure. My measure is preferable for two reasons. First, deflated revenues are intended to proxy relative value units. Commuting actual RVUs avoids the proxy measure. Second, prices as financial incentives are important covariates to be studied. Using deflated revenues introduces measurement error which confounds estimation of their causal effect.

Three other measures of practice patterns do not require RVU input-output data. The number of procedures offered is measured by the count of unique CPT codes supplied. Next, the physician's procedural specialization is measured by the Herfindahl-Hirschman index (HHI) of the bundle supplied, using each procedure's share of total billings.[27] The HHI ranges from $(0, 1]$ and measures the concentration of billing practices. Last, I measure the physician's tendency to supply services in an outpatient setting by the facility fraction of total billings.

[26] CMS does not pay physicians for practice expense RVUs when service is supplied in a facility setting, instead paying the hospital under a different payent mechanism. To construct a consistent measure of utilized inputs and output, I use metrics from the physician office setting.

[27] Thanks to Aviv Nevo for suggesting this practice pattern measure. Notating procedures by k and the observed set of offerings by K, following the standard formula: $\text{HHI} = \sum_{k \in K} (\frac{\text{billings}_k}{\sum_{k \in K} \text{billings}_k})^2$

8.2.3 Details on financial incentives

I begin my measurement strategy with Medicare's FFS revenue formula:

$$\text{Revenue} = \text{“conversion factor”} * [(\text{Work GPCI}) * \text{“Physician work RVUs”} +$$

$$(\text{PE GPCI}) * \text{“Practice expense RVUs”} + (\text{Malpractice GPCI}) * \text{“Malpractice RVUs”}]$$

In this formula, the GPCI stands for Geographic Practice Cost Index, and RVUs are the output index. The GPCI is how the regulator adjusts prices across Medicare Localities. The are 89 Medicare Localities defined by states, and by subdivisions of states for areas with large populations. The GPCI is a weighted average of input factor prices which vary at the county level. The "conversion factor" is Medicare's national mean price per RVU. In 2012 the price was $34.023 per RVU, and $35.8228 per RVU by 2015.

As with RVUs, there are three GPCI components. First is physicians labor. The "work GPCI" adjusts the baseline price per RVU for variation in physician wages across locations. Second is the "practice expense" (PE) component accounts for equipment and other capital expenses, overhead, and other practice costs associated with a CPT service. The PE GPCI adjusts this payment across Medicare localities for variation in office rental rates, and input price variation other than the physician's labor. Last, the malpractice component is a risk adjustment; the GPCI accounts for variation in medical malpractice insurance premiums across states.

I gather GPCI data from CMS's Physician Fee Schedule Federal Regulation Notices and Relative Value Files over 2011-2017. These files provided GPCIs at the Medicare Locality level for each year. In 2012, 2014, and 2017 the regulator included the county level input price indices from which the GPCIs were derived. I interpolate 2013 from 2012 and 2014 cost data, and assign 2017 values to 2015. Other imputation strategies were considered, but since there is little time series variation in county factor prices the differences are negligible.

I combine the three GPCIs into a single measure of payment generosity and cost. The "Geographic Adjustment Factor" (GAF) is a summary measure used by CMS for this task. The GAF formula is

$$\text{GAF} = (\text{work GPCI}) * .48266 + (\text{PE GPCI}) * .47439 + (\text{malpractice GPCI}) * .04295$$

The weights on each component are national average cost shares in 2012. I measure the physician's Medicare payment incentive by the GAF for each Medicare Locality in each year. The Medicaid payment incentive is measured as a fraction of the average Medicare payment rate in the physician's state. This fraction was measured by the Urban Institute in 2014, and is not available over time. I interact the Urban Institute measure with state average Medicare GAF to capture Medicaid's state-level regulatory scheme.

I construct the county level GAF from the factor cost indices as a measure of local practice costs. Finally, primary care physicians receive a 10 percent "bonus" from Medicare for practicing in designated zip codes. I measure this incentive directly as an indicator variable from the physician's location data.

8.3 Mover and non-mover differences

Appendix Table 8.3 Summary statistics for movers and nonmovers

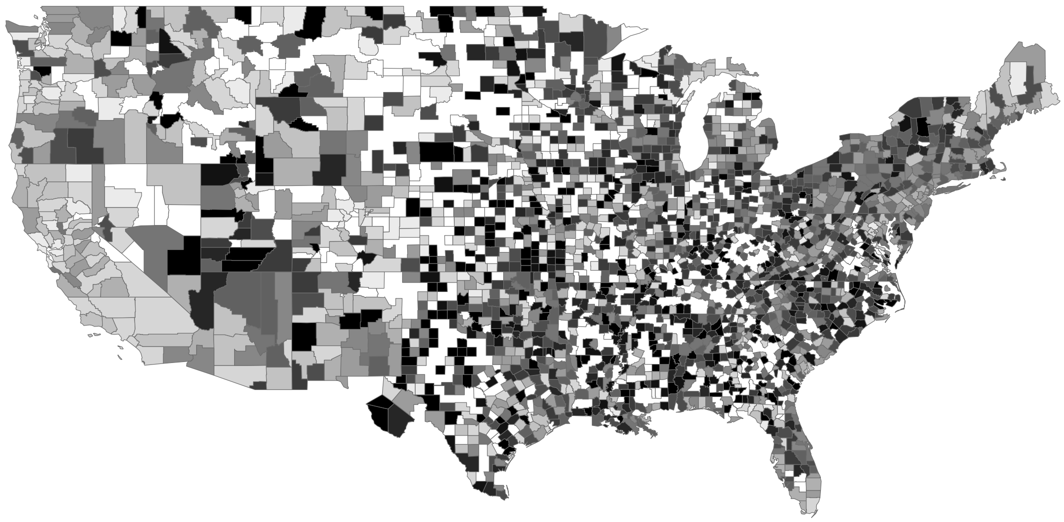
	Nonmovers		Movers		
	Mean	St. Dev.	Mean	St. Dev.	Δz [a]
Physician characteristics:					
Female	0.32	0.47	0.41	0.49	0.14
Sole proprietor	0.23	0.42	0.22	0.41	-0.02
General Internal Medicine [b]	0.36	0.48	0.41	0.49	0.09
Family Practice	0.32	0.47	0.33	0.47	0.01
Accept Medicare	0.69	0.46	0.68	0.46	-0.04
Accept Medicaid	0.61	0.49	0.60	0.49	-0.02
Medicaid fraction	0.27	0.21	0.29	0.20	0.22
Medicare revenue ($)	169,226.6	296,106.8	114,737.6	219,886.3	-0.05
Patients	416.05	466.79	332.92	363.11	0.03
Facility fraction	0.40	0.42	0.52	0.44	0.23
Patient demographics:					
Average age	71.60	4.93	70.80	5.08	-0.59
Fraction female	0.55	0.15	0.54	0.16	-0.34
Fraction black	0.08	0.16	0.07	0.16	-0.02
Health risk (HCC score)	1.73	0.90	1.86	0.88	0.19
Alzheimers	0.14	0.13	0.15	0.14	-0.01
Arthritis	0.38	0.14	0.39	0.14	-0.08
Asthma	0.08	0.07	0.09	0.07	0.03
Atrial fibrillation	0.13	0.10	0.14	0.11	-0.06
Cancer	0.11	0.10	0.11	0.11	-0.10
Depression	0.25	0.13	0.29	0.14	0.19
Diabetes	0.37	0.15	0.38	0.16	-0.02
Heart failure	0.27	0.18	0.30	0.20	0.05
Hyperlipidemia	0.56	0.15	0.56	0.16	-0.07
Hypertension	0.68	0.12	0.69	0.12	-0.02
Ischemia	0.42	0.19	0.43	0.20	-0.01
Kidney disease	0.30	0.19	0.33	0.20	0.09
Obstructive pulmonary	0.20	0.14	0.23	0.15	0.08
Osteoporosis	0.08	0.07	0.08	0.07	-0.04
Schizophrenia	0.05	0.07	0.06	0.07	0.08
Stroke	0.06	0.07	0.07	0.07	-0.03

Notes: Author's calculations from physician microdata.
[a] Difference of normalized means: $\Delta z := \frac{\text{mean movers}}{\text{st. dev. movers}} - \frac{\text{mean nonmovers}}{\text{st. dev. nonmovers}}$.
[b] Omitted category is General Practice + Internal Medicine sub-specialties.

8.4 Illustrations of geographic variation in primary care

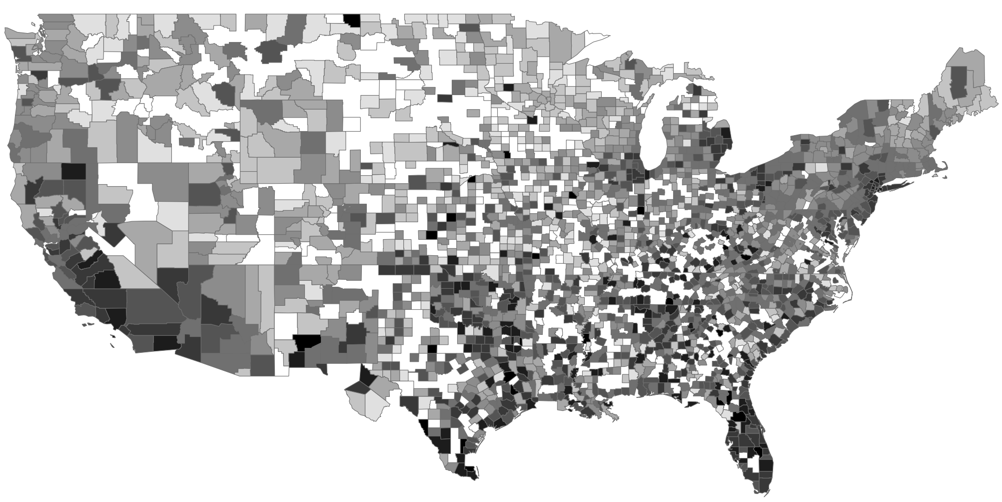
8.4.1 Acceptance and capacity

Figure 21: Geographic variation in acceptance of Medicaid Dual Eligibles



Notes: County average Medicaid Dual Eligible acceptance rate in 2014. Lightest areas have a 0-25% acceptance rate, darkest areas have 90+% acceptance, areas mapped without borders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.

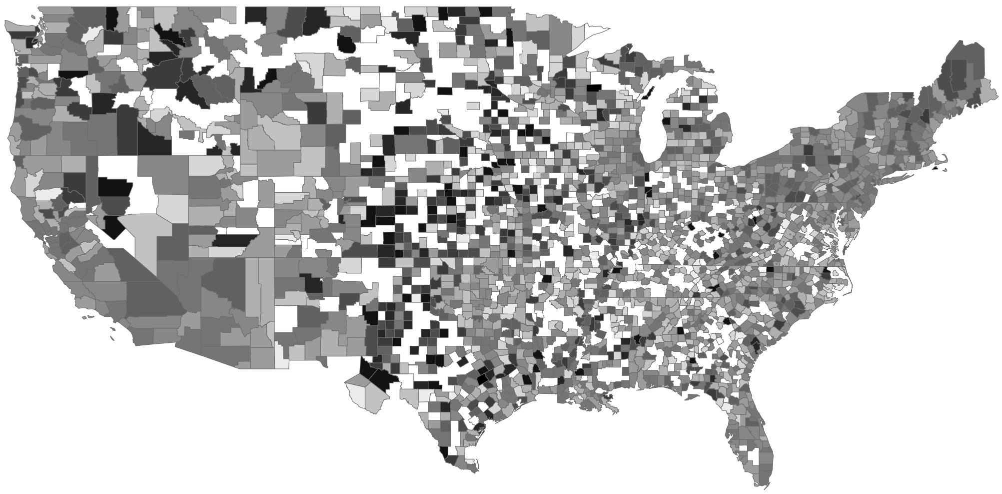
Figure 22: Geographic variation in total output capacity for Medicare/Medicaid



Notes: County average physician output capacity for Medicare and Medicaid Dual Eligible patients in 2014, measured by total Relative Value Units (RVUs) supplied. Areas mapped without borders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.

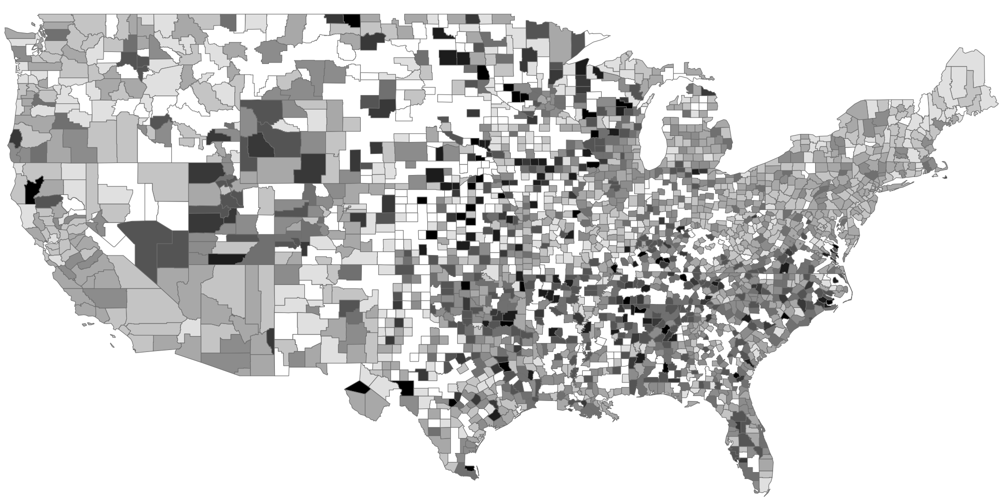
8.4.2 Practice patterns

Figure 23: Geographic variation in physician labor to capital ratios



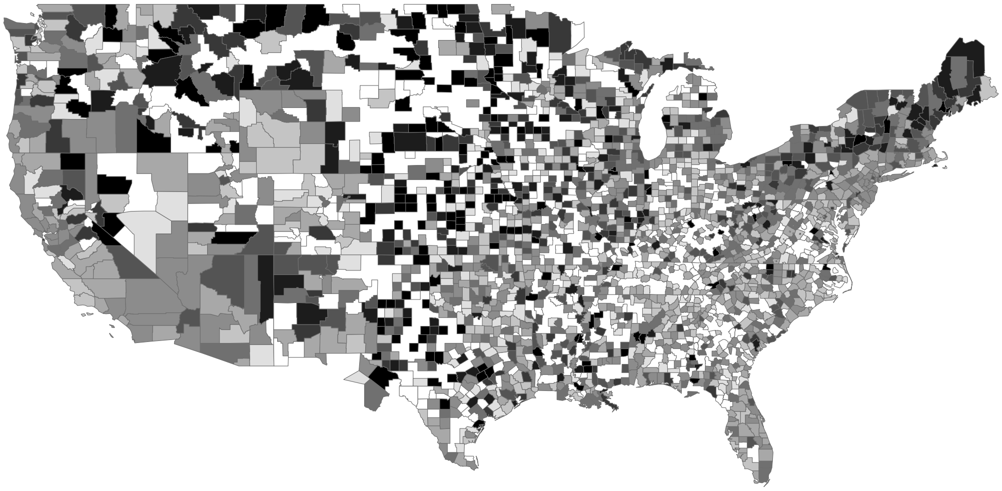
Notes: County average physician labor minutes per equipment use. Lightest areas are 1-5 minutes labor/capital, darkest areas 90+ minutes labor/capital, areas mapped without borders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.

Figure 24: Geographic variation in the number of procedures offered to Medicare/Medicaid



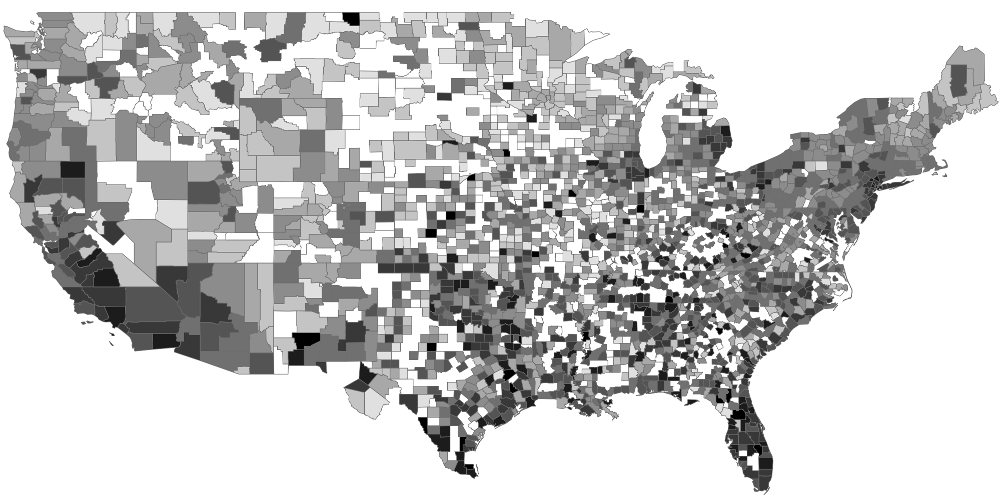
Notes: County average number of unique procedures offered by physicians in 2014 to Medicare and Medicaid Dual Eligible consumers. Areas mapped without borders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.

Figure 25: Geographic variation in physician facility use



Notes: County average facility share in 2014, measured by the physician's fraction of total billings in an outpatient facility. Lightest areas have a 1-10% facility share, darkest areas a 90-100% facility share, areas mapped without borders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.

Figure 26: Geographic variation in output (RVUs) per patient



Notes: County average output per patient in 2014, measured by physician Relative Value Units (RVUs) supplied per unique Medicare/Medicaid beneficiary. Areas mapped without borders are counties with no primary care physicians in the NPPES database in 2014. Source: Author's calculations from physician microdata.