Determinants of Low-Cost Provider Use: Evidence from Lab Tests *

Calvin A. Ackley†

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Abstract

Importance: Medical service prices vary substantially in the United States, even within small geographic regions. Insurers have increasingly used transparency tools and plan incentives to steer patients toward lower-cost providers. However, the evidence on the effectiveness of these initiatives is mixed, and there remains considerable uncertainty on the determinants of provider choice.

Objective: To measure price variation across lab providers and study the factors associated with low-cost lab use.

Design: I measure lab prices at both hospital-based and independent providers, and calculate the savings available by redirecting demand toward non-hospital-based facilities. I then link lab visits to likely referring providers, primary care providers, and other plausible explanatory variables. Using this information, I conduct an analysis of variance for per-lab spending and site of care. Leveraging patients with visits across multiple referring providers, I estimate the impact of referring providers on payments and independent lab use. I also link information on hospital ownership of physician practices to assess the role of vertical integration in driving patient flows.

Main Outcome Measures: Provider-level prices, spending per lab, out-of-pocket spending per lab, use of non-hospital-based lab providers, regression partial R^2

Results: Independent lab prices are, on average, 70%-80% less than hospital-based lab prices, implying that considerable savings can be achieved by steering patients toward non-hospital-based facilities. Referring physicians are the strongest determinant of per-lab spending and hospital-based use. Likely referrers explain 73% of the explained variance in independent lab use, and 34% of the total variance. Primary care providers are similarly predictive of spending and site of care. Switching from a referrer in the bottom quintile of independent lab propensity to one in the top quintile is associated with a 39% drop in spending per test. Vertically integrated providers are less likely to be associated with independent lab use, and are instead associated with higher spending per test.

Conclusions and Relevance: Considerable savings can be achieved by reallocating lab services from hospital-based facilities to independent providers. However, established physician relationships, referral dynamics, and vertical integration likely act to impede this type of price shopping. This suggests that strong incentives and engagement from both patients and physicians are required in order to stimulate greater price responsiveness for shoppable services. Pairing physician-side incentives with designs like reference pricing and tiered networks may help reduce per-unit costs.

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†U.S. Bureau of Economic Analysis, Suitland, MD. Calvin.Ackley@bea.gov

1 Introduction

Medical service prices vary substantially in the United States, both across and within geographic areas.[1, 2] This is true for even the most homogeneous services such as diagnostic imaging and lab tests. Lower-limb MRI prices vary as much as twelve-fold across the country and lipid panel prices vary by a factor of ten within the state New Hampshire alone.[1, 3] For these services, price differences are particularly salient between hospital-based and non-hospital-based providers.[4, 3] Interestingly, prices vary not only across providers, but across insurers for the same provider.[5, 2]

In response to these rising and disperse prices, employers and insurers have increasingly sought to deploy cost-sharing incentives to steer patients toward lower-cost providers. Plan designs of this fashion include high-deductible health plans (HDHPs), consumer-directed health plans (CDHPs), tiered networks, and reference pricing. More generally, out-of-pocket spending, especially in the form of deductibles, has increased markedly over the last two decades.[6, 7] To pair with cost-sharing incentives, many insurers have developed price transparency tools to help patients identify low-cost providers.

Despite the proliferation of transparency tools and innovative designs, the evidence on the effectiveness of these efforts is decidedly mixed. For HDHPs and CDHPs, which both rely on a high deductible, the evidence indicates that these designs generally fail to meaningfully stimulate price shopping.[8, 9, 10, 11]. The evidence on tiered designs and reference pricing is somewhat more favorable, although documented effects sizes are typically modest.[12, 13, 14, 15, 16, 17, 3] On transparency tools, research suggests that they can be effective, but that few people actually use them.[18, 19, 20, 21, 22, 23, 24] On balance, it is clear that stimulating price shopping is difficult, and that there is more to understand about the dynamics of patient demand.

In this paper, I seek to develop further insight into the consequences and determinants of price shopping for medical care by studying where patients receive lab tests. Lab tests are the most voluminous medical procedure in the United States and are, for several reasons, a prime candidate for fruitful steering interventions.[25] Most prominently, lab prices vary markedly across providers, especially between hospital-based and independent (non-hospital-based) facilities. In my sample, for example, the average price of a lipid panel is 76% less at a non-hospital-based provider than at a hospital-based one ($15 at independent labs vs. $62 at hospital-based providers). Given this dichotomy, both insurers and patients have an easy rule-of-thumb for identifying more-expensive and less-expensive providers.[1] In addition, labs can generally be scheduled in advance, and are regulated in quality by the Centers for Medicare & Medicaid Services.

As a result of these factors, considerable savings can be achieved by moving demand toward non-hospital-based labs. Several insurers have, in fact, accomplished this to some extent using reference pricing and tiered designs. For example, Robinson et. al (2016) report that a reference pricing program introduced by a large firm achieved a 32% reduction in the amount paid per lab.[26] Similarly, Ackley (2024) finds that a tiered-type design led to a 6%-12% increase in the likelihood of non-hospital-based lab use.[3]

In my setting, all consumers have access to a statewide transparency tool, and many have access to insurer-specific tools. In addition, deductible levels are generally high, and many patients are enrolled in tiered-type plans that explicitly incentivize non-hospital-based lab use.[27, 28, 3] Despite this, less than half of labs are performed at independent facilities, suggesting that other factors like integrated provider networks and referrals may be important. I document the excess costs that result from this and shed light on the role of these other factors.

[1] A similar dichotomy exists between hospital-based and ambulatory surgery center-type facilities for outpatient surgical procedures and imaging.[15, 4, 17]

2 Data

The primary data source for this study is the New Hampshire All Payer Claims Database. This database is maintained as part of the New Hampshire Comprehensive Health Care Information System (NHCHIS). The use of this de-identified data for the purpose of this study was approved by the New Hampshire Department of Health and Human Services Claims Data Release Advisory Committee. These data contain detailed information on the patient, plan, provider, and payer associated with medical claims in the state. I use commercial claims associated with the State's three largest insurers, Anthem, Harvard Pilgrim Health Care, and Cigna, spanning 2010 to 2015. An interesting feature of this setting is that many patients are subject to tiered cost sharing arrangements which heavily incentivize independent lab use. In these plans, patients have no out-of-pocket costs when they use independent labs, but face a deductible at most hospital-based facilities.[2] By the end of 2015, around 72% of the small-group market and 42% of the large-group fully insured market were exposed to tiered designs operated by Anthem or Harvard Pilgrim.[29]

2.1 Primary Lab Samples

To construct my primary sample of lab tests, I first use the CPT/HCPCS code on each claim to pull the 200 most common lab tests in the state. This sample accounts for around 90% of the total spending on tests. In some analyses, I restrict attention to a subset of 97 blood tests that are commonly performed at both hospital-based and independent labs.[3] Each lab claim includes information on the charge amount, the amount paid by the insurer, and the out-of-pocket price paid by the patient. I construct the total negotiated price associated with each claim as the sum of the insurer paid amount and the total out-of-pocket price paid by the patient. Negotiated prices vary markedly across procedures, across providers, over time, and across insurer contracts. I discard labs that occurred during an inpatient stay as patients are unlikely to be able to shop for care in this circumstance.

2.2 Patient and Plan Information

For the patient associated with each lab claim, I identify demographic information such as age, sex, and zip code of residence. Additionally, I use patient-level diagnosis histories to construct a Charlson Comorbidity Index for each individual. I use annual enrollment information to identify plan information for each patient. This includes details on the carrier (Anthem, Harvard Pilgrim, or Cigna), market category (individual, small, or large), plan type (HMO, PPO, etc.), and contract type (fully insured or self-insured/administrative services only). I define a plan as a unique combination of these four identifiers. Negotiated prices are nearly constant within a plan-provider-year cell, but generally vary across each of these components.[1, 5, 3]

2.3 Provider Information

Each lab claim contains provider identifiers that can be linked to detailed provider-level information such as address, specialty, tax identification number, and facility name. I keep lab claims associated with the 25 most common providers, and one additional independent provider, who collectively account for over 95% of the total lab volume over the sample period. For this sample of providers, I construct an

[2] Ackley (2024) describes and analyzes Anthem's plan, called the "Site of Service" design, in more detail.

[3] Additional details, and a complete listing of these procedure codes and summary statistics, are given in the appendix.

identifier distinguishing hospital-based labs from independent labs. The most common non-hospital-based lab is Quest Diagnostics, which has multiple locations across the state.

2.4 Identifying Likely Referrers and Primary Care Physicians

In addition to utilizing patient and plan information, I link individual lab visits to likely referring providers. Labs are typically ordered by a physician, and these physicians are in a strong position to influence patient choice. A recent study of MRI use identified referring providers to be the strongest determinant, by far, of MRI location, but this area is relatively understudied given its potential importance.[4][4] To develop a likely-referrer identifier for each lab, I look for primary care and specialist visits that occur in the time period directly proceeding the lab. Specifically, I identify all evaluation and management (E&M) visits that take place in the 30-day period leading up to the lab.[5] Among lab visits that have a matching E&M case, the match is unique in 70% of visits. In these cases, I define the likely referrer as the physician on that claim. For labs that match multiple E&M claims in the 30-day window, I define the likely referrer as the physician that appears in closest proximity to the lab date.[6] This approach is similar to that used by Chernew et al. (2021) to identify referring orthopedists for MRI scans.

I also construct a primary care provider (PCP) identifier for each patient in the sample. PCPs may be important because they can both order labs and refer patients to specialists who order them. In this way, PCPs are quite plausibly a significant upstream determinant of lab use and other care. For each patient-year, I define the PCP as the primary care physician responsible for the most visits in that year.[7] For patient-years without any primary care visits, I use the most recent PCP identifier associated with that patient.[8]

For both likely referrers and PCPs, I construct a vertical integration flag that identifies whether or not a physician is associated with a vertically integrated hospital system. To do so, I use both tax identification numbers as well as ownership information from the SK&A physician database. I define physicians to be vertically integrated if they share a tax ID with a hospital or if their practice is reported as being owned by a hospital or hospital system in the SK&A data.

3 Methods

3.1 Independent Lab Savings

I first summarize the price differences between hospital-based providers and independent labs. I compute the mean price paid for each provider and procedure, as well as the volume-weighted price across all hospitals and across all independent labs. I define the independent lab discount as the difference between the weighted-average hospital price and the weighted average non-hospital price. I compute the independent lab discount for each procedure separately and compute an aggregate measure as the volume-weighted average across procedures.

[4]Several surveys also implicate the importance of referring physicians.[30, 31]

[5]I define an E&M visit as a unique combination of patient-physician-date that has an accompanying CPT/HCPCS code for office evaluation and management (99201, 99202, 99203, 99204, 99205, 99211, 99212, 99213, 99214, 99215)

[6]In 92% of cases, patients have just one physician per day with an E&M claim. For patient-days where there are multiple physicians with an E&M claim, I keep the provider who is responsible for the most claims or, if there is still a tie, the most payments.

[7]I define primary care visits as an office E&M visit with a physician whose speciality is listed as family practice, internal medicine, general practice, pediatric medicine, physician assistant, or nurse practitioner.

[8]For example, if a patient sees PCP X in 2009 and 2012, and PCP Y in 2014 and 2015, then I define their PCP as X for 2009-2013 and as Y for 2014-2015.

I also compute a measure of the total savings available from independent lab usage. To do this, I calculate the difference between the actual price paid and the mean non-hospital price for each lab procedure performed at a hospital in the sample. I then add up the available savings across all instances. I perform this calculation separately for each procedure and also compute an aggregate measure summed across all 200 procedures in the main sample.

3.2 Factors Associated with Independent Lab Use

Motivated by the considerable price differences between hospital-based and independent labs, I next perform an analysis of variance ANOVA to assess factors associated with independent lab usage. I consider two dependent variables for this ANOVA. The first is an indicator that is equal to 1 if the lab is performed by an independent facility and equal to 0 if the lab is performed by a hospital-based facility. The second is the log of the total amount paid for the lab. For dependent variables, I consider age, sex, Charlson score, zip code, month, year, plan, and either the likely-referrer ID or the patient's primary care provider ID. In the ANOVA, I group age, sex, and Charlson score together under the heading *demographics*.

Using these dependent and independent variables, I estimate regressions of the following form:

$$y = \beta demo + \theta^{zip} + \theta^{plan} + \theta^{time} + \theta^{proc} + \theta^{prov} + \epsilon \tag{1}$$

Patient zip code captures the distance to various providers as well as socioeconomic factors that may be correlated with provider choice. Plan fixed effects capture aspects of cost sharing and provider network breadth that vary across plans. Plan fixed effects also reflect insurer-level information such as bargaining power, which may be related to negotiated prices. Likely-referrer fixed effects capture the relationship between the physician who likely ordered the lab work and the lab facility that performed the service. Likely referrers may explicitly direct patients toward a particular lab, or patients may seek out labs that are affiliated with their providers. The influence of PCPs may be even more broad, as PCPs may send patients to specific labs or refer patients to specialists who then exert influence on lab use.

I use the full model (1) to compute the regression partial R^2 for each of the independent variable components on the right-hand of the equation.[9] I estimate two separate iterations of partial R^2s, one using the sample of labs with a matching likely referrer, and one using the sample of labs with a matching PCP. Additionally, for this and subsequent analysis, I restrict attention to the subsample of common blood tests. These tests are routinely performed at both hospital-based and independent labs, and are frequently subject to cost sharing.[10] I compute bootstrap standard errors for each R^2 estimate.

3.3 Specific Impact of Primary Care and Likely Referring Providers

I next examine the impact of likely referrers and PCPs in more detail, given their evidently high leverage in this setting. I first derive physician-level estimates of independent lab propensity.

To do so, I obtain the estimated provider fixed effects $\hat{\theta}^{prov}$ from the full regression model (1), where the dependent variable is an independent lab indicator. These provider-level fixed effects capture the correlation between patients' physicians and independent lab use, adjusted for differences in patient characteristics and the composition of labs obtained. I translate these estimates into a more interpretable measure by ordering the sequence of $\hat{\theta}^{prov}$'s and computing each provider's percentile rank out of 100.

[9] I also consider an alternative, but similar, approach in which I sequentially estimate regressions, adding an additional independent variable each time and tracking the change in the total R^2. This method produces qualitatively-similar estimates.

[10] Additional details on sample construction are given in the appendix. The main results are robust to alternative sample constructions.

I refer to this measure as the non-hospital use index (NHUI). I compute this index separately for likely referrers and PCPs.

Physicians with a high NHUI are more likely to have patients who use non-hospital based labs. To examine the consequences of seeing these providers versus providers with a lower NHUI, I estimate a modified version of model (1)

$$y = \sum_{j=2}^{5} \delta_j^{NHUI} + \theta^{time} + \theta^{proc} + \theta^{patient} + \epsilon \tag{2}$$

This model includes quintiles of the likely referrer's NHUI as well as patient-level fixed effects $\theta^{patient}$. The patient fixed effects are critical here because patient preferences may be correlated with provider referral patterns. That is, patients who prefer a particular hospital may also prefer to use hospital-affiliated physicians and labs. By including patient fixed effects, I leverage patients who had multiple lab visits across different likely referrers over the sample period. This helps differentiate patient preferences from the influence of physicians. Given that this model relies on patients with multiple visits across physicians, I estimate it for the likely-referrer-linked sample but not for the PCP-linked sample. I consider three outcomes of interest for model: the log of total payments, the out-of-pocket price, and an independent lab indicator. Given that the out-of-pocket price is frequently zero, I estimate the regression for out-of-pocket price using a generalized linear model with a log link function.

3.4 Vertical Integration

A recent body of work indicates that the vertical integration of physician practices and hospitals has become increasingly common, and that this arrangement is associated with higher prices.[32, 33, 34, 1] Vertical integration has a plausibly significant role in lab demand because hospital systems can own both physician practices and labs. Therefore, integrated hospital systems have a financial incentive to encourage referring physicians to direct patients toward hospital-owned labs. This dynamic applies to PCPs as well, who may be directed to steer patients toward specialists and labs within the hospital system.

To examine the role of vertical integration in shaping lab use, I first compute the share of physicians in each percentile of the NHUI distribution who are vertically integrated with a hospital. I do this for both likely referrers and PCPs. I next estimate a modified version of the regression model (2), which includes an indicator variable for vertical integration. This model excludes the NHUI quintiles but maintains patient fixed effects. Similar to the prior model, this setup leverages patients who have multiple lab visits tied to both vertically integrated and non-vertically integrated physicians.

4 Results

The top panel of Figure 1 shows the average price of a lipid panel for all hospital-based and independent labs in the sample. As the figure shows, independent labs have strictly lower prices than hospital-based providers across the board. The most expensive hospital-based labs are around five-times costlier than non-hospital-based labs. The bottom panel of Figure 1 plots the volume-weighted mean price for both hospitals and independent labs across the 50 most common tests. As this figure depicts, price differences are large and relatively uniform across tests.

Table 1 shows the independent lab discount and total savings available for the 10 most common tests and an aggregate measure across all tests in the sample. The average discount across all labs is 74%, and does not vary much across tests. If every hospital-based lab was instead priced at the independent lab level the resulting savings would be about $333.37 Million. This translates to about $253 per person-year, for those persons who get at least one lab in the year. The savings available from lipid panels alone is about $20 per person-year.

Table 2 presents the partial R^2 estimates for each independent variable group in model (1). The first two columns present results for the models that use the likely referrer ID as the provider ID. For both outcomes, likely-referrer fixed effects explain significantly more of the variance than any other variable. For the independent lab outcomes, likely-referrer fixed effects explain about 34% of the total variance, and about 73% of the explained variance. Plan fixed effects have the second-largest partial R^2 estimate, and only explain about 2% of the total variance. For the total payment amount, likely-referrers explain about 22% of the total variance, with plan effects explaining about 3%. Importantly, because likely referrers are measured with some noise, these estimates are probably a slight underestimate of the true share explained by referrers.

The last two columns of Table 2 present the partial R^2 estimates for the models which include the patient's PCP ID. Here still, the PCP fixed effects explain, by far, the most variance of any of the independent variables. For the independent lab outcome, PCP fixed effects explain about 21% of the total variance and 56% of the explained variance. For the total payment amount, PCPs explain about 14% of the variance. By comparison, plan fixed effect explain about 3% of the variance for each outcome. Appendix Tables 2-5 present the results from an alternative approach, where I iteratively add independent variables to to the regression and track the changes in R^2. These results are qualitatively very similar to the partial R^2 results.

Table 3 presents the regression results associated with model (2), where the independent variables of interest are quintiles of the likely-referrers NHUI. Having a likely referrer in the fourth quintile of the NHUI distribution is associated with about a 10% reduction in spending per lab test, relative to a provider in the first quintile. More dramatically, having a provider in the fifth quintile is associated with a 39% cut in spending per test.[11] Importantly, this translates into out-of-pocket savings for patients. A likely referrer in the fifth quintile is associated with 43% less in out-of-pocket spending per test.[12] Unsurprisingly, a fourth-quintile referrer increases the probability of using an independent lab by 8.8 percentage points, while a fifth-quintile referrer increases the probability by 36.3 percentage points.

The top panel of Figure 2 plots the share of likely-referring physicians that are vertically integrated for every percentile of the NHUI. The bottom panel presents the analogous plot for primary care providers. Both plots show a similar pattern of vertical integration rates that decline as the non-hospital-based lab propensity, measured by the NHUI, increases. In other words, vertically integrated physicians are more likely to be associated with hospital-based lab use than non-vertically integrated physicians. This relationship is particularly salient when comparing the top and bottom regions of the NHUI distribution. Among likely-referrers in the bottom quartile of the NHUI distribution, around 75% are vertically integrated with hospitals. In contrast, the share of vertically integrated providers ranges from about 0%-25% among those in the top quartile. These contrasts are roughly the same for primary care providers.

Table 4 presents the regression results for the modified version of model (2), where the key independent variable is an indicator for vertical integration of the likely referrer. For this model, I maintain individual fixed effects, meaning that estimates depend on patients with visits across both vertically-integrated and non-vertically-integrated referrers. Overall, vertically-integrated referrers are associated with a higher likelihood of hospital-based lab use, higher total payments, and higher out-of-pocket payments. Specifi-

[11] Regression coefficients are converted to percentage changes via the transformation $\exp(\hat{\theta}) - 1$

[12] The reason why the estimated effect for out-of-pocket spending is slightly larger in percentage terms than the effect for total spending is likely because the distribution of out-of-pocket costs contains many zeros. This reduces the amount of variation in the outcome variable across individuals' visits.

cally, vertically-integrated referrers are associated with a 6.2 percentage point decrease in the likelihood of using an independent lab, and about a 7.9% increase in payments per lab. These results are consistent with the correlation shown in Figure 2.

5 Discussion and Conclusions

There are three main implications of these findings. First, considerable savings can be achieved by reallocating lab services from hospital-based facilities to independent providers. Second, upstream physician relationships, such as PCPs and referring specialists, are the strongest determinant of spending and site of care for lab tests. Third, vertical integration between physicians and hospitals bolsters the flow of services toward hospitals, at a significant per-unit expense to insurers and patients.

These implications are highly relevant for insurers, policymakers, and patients interested in reducing spending without compromising on quality of care. While this paper focuses specifically on lab tests, these results are applicable to a broader range of services, especially those that are similarly shoppable such as imaging and ambulatory surgeries. Indeed, Chernew et al. (2021) present similar findings on the primacy of referrers for lower-limb MRI scans.[4]

Many insurers have focused on patient-centered incentives such as high deductibles, tiered cost sharing, and reference pricing as a way to save money through site-of-care differentials. While several of these programs have had some degree of success, my findings indicate that established physician relationships and referral dynamics are probably functioning as a considerable barrier to steering and price shopping. While this presents a challenge in terms of plan design, it may also present an opportunity to stimulate price-shopping by targeting upstream physicians who are responsible for orders and referrals. On this point, several studies show that directly incentivizing physicians to be mindful of patient costs can lead to substantial savings.[35, 36] Combing physician-side incentives with designs like reference pricing and tiered networks may help curb per-unit costs for shoppable services.

The design of patient and physician incentives has become even more important in the face of increasing consolidation in the health care industry. Vertical integration of hospitals and physicians has risen considerably in the last two decades, and is generally associated with higher prices.[32, 33, 34, 1] My results shed light on a key mechanism through which vertical integration generates upward pricing pressure, and highlights that challenge faced by insurers and policymakers in achieving cost savings through steering.

Directing patients who see vertically-integrated physicians away from hospital-based lab, imaging, and ambulatory surgical care appears to be quite challenging. However, the gains from doing so, either through patient or physician incentives, can be quite large. In addition to the direct per-unit savings associated with non-hospital-based sites of care, there can be indirect savings through negotiated price dynamics. Indeed, a theoretical and empirical literature indicates that increasing the steering capacity of plans leads to lower prices in general.[37, 24, 38, 39, 3] As patients become more responsive to price differences between providers, providers have greater incentive to negotiate lower prices. My results suggest that meaningfully augmenting price responsiveness probably requires strong incentives and engagement from both patients and physicians.

References

[1] Cooper Zack, Craig Stuart V, Gaynor Martin, Van Reenen John. The price ain't right? Hospital prices and health spending on the privately insured *The quarterly journal of economics.* 2019;134:51–107.

[2] Sinaiko Anna D, Kakani Pragya, Rosenthal Meredith B. Marketwide price transparency suggests significant opportunities for value-based purchasing *Health Affairs.* 2019;38:1514–1522.

[3] Ackley Calvin A. The Impact of Preferred Provider Incentives on Demand and Negotiated Prices *American Journal of Health Economics, Forthcoming.* 2024.

[4] Chernew Michael, Cooper Zack, Hallock Eugene Larsen, Morton Fiona Scott. Physician agency, consumerism, and the consumption of lower-limb MRI scans *Journal of Health Economics.* 2021;76:102427.

[5] Craig Stuart V, Ericson Keith Marzilli, Starc Amanda. How important is price variation between health insurers? *Journal of Health Economics.* 2021;77:102423.

[6] Rae Matthew, Copeland Rebecca, Cox Cdynthia. Tracking the rise in premium contributions and cost-sharing for families with large employer coverage 2019. Accessed: 2024-07-08.

[7] Claxton Gary, Rae Matthew, Winger Aubrey, Wager Emma. Employer Health Benefits Survey 2023 Annual Survey tech. rep.Kaiser Family Foundation 2023. Accessed: 2024-07-08.

[8] Haviland AM, McDevitt R, Sood N, others . Healthcare spending and preventive care in high-deductible and consumer-directed health plans. *The American journal of managed care.* 2011;17:222–230.

[9] Sood Neeraj, Wagner Zachary, Huckfeldt Peter, Haviland Amelia M. Price shopping in consumer-directed health plans in *Forum for Health Economics and Policy*;16:35–53De Gruyter 2013.

[10] Haviland Amelia M., Eisenberg Matthew D., Mehrotra Ateev, Huckfeldt Peter J., Sood Neeraj. Do "Consumer-Directed" health plans bend the cost curve over time? *Journal of Health Economics.* 2016;46:33 - 51.

[11] Brot-Goldberg Zarek C, Chandra Amitabh, Handel Benjamin R, Kolstad Jonathan T. What does a deductible do? The impact of cost-sharing on health care prices, quantities, and spending dynamics *The Quarterly Journal of Economics.* 2017;132:1261–1318.

[12] Sinaiko Anna D, Rosenthal Meredith B. The impact of tiered physician networks on patient choices *Health Services Research.* 2014;49:1348–1363.

[13] Frank Matthew B, Hsu John, Landrum Mary Beth, Chernew Michael E. The impact of a tiered network on hospital choice *Health services research.* 2015;50:1628–1648.

[14] Robinson James C, Brown Timothy T, Whaley Christopher, Finlayson Emily. Association of reference payment for colonoscopy with consumer choices, insurer spending, and procedural complications *JAMA Internal Medicine.* 2015;175:1783–1789.

[15] Whaley Christopher M, Guo Chaoran, Brown Timothy T. The moral hazard effects of consumer responses to targeted cost-sharing *Journal of Health Economics.* 2017;56:201–221.

[16] Prager Elena. Healthcare Demand under Simple Prices: Evidence from Tiered Hospital Networks *American Economic Journal: Applied Economics.* 2020;12:196–223.

[17] Ackley Calvin A. Tiered cost sharing and health care demand *Journal of Health Economics.* 2022;85:102663.

[18] Whaley Christopher, Chafen Jennifer Schneider, Pinkard Sophie, et al. Association between availability of health service prices and payments for these services *Jama.* 2014;312:1670–1676.

[19] Lieber Ethan MJ. Does It Pay to Know Prices in Health Care? *American Economic Journal: Economic Policy.* 2017;9:154–79.

[20] Desai Sunita, Hatfield Laura A, Hicks Andrew L, Chernew Michael E, Mehrotra Ateev. Association between availability of a price transparency tool and outpatient spending *Jama.* 2016;315:1874–1881.

[21] Desai Sunita, Hatfield Laura A, Hicks Andrew L, et al. Offering a price transparency tool did not reduce overall spending among California public employees and retirees *Health Affairs.* 2017;36:1401–1407.

[22] Mehrotra Ateev, Dean Katie M, Sinaiko Anna D, Sood Neeraj. Americans support price shopping for health care, but few actually seek out price information *Health Affairs.* 2017;36:1392–1400.

[23] Brown Zach Y. Equilibrium effects of health care price information *Review of Economics and Statistics.* 2019;101:699–712.

[24] Brown Zach Y. An empirical model of price transparency and markups in health care *Manuscript.* 2019.

[25] Song Zirui, Lillehaugen Timothy, Wallace Jacob. Out-of-network laboratory test spending, utilization, and prices in the US *JAMA.* 2021;325:1674–1676.

[26] Robinson James C, Whaley Christopher, Brown Timothy T. Association of reference pricing for diagnostic laboratory testing with changes in patient choices, prices, and total spending for diagnostic tests *JAMA Internal Medicine.* 2016;176:1353–1359.

[27] Tu Ha, Gourevitch Rebecca, others . Moving markets: lessons from New Hampshire's health care price transparency experiment tech. rep.Mathematica Policy Research 2014.

[28] Smagula Jennifer, Gorman Don, Lockhart Gabriella, Kiene Linda, Gorman Bela. Final Report of the 2016 Health Care Premium and Claim Cost Drivers 2017.

[29] Smagula Jennifer, Gorman Don, Lockhart Gabriella, Kiene Linda, Gorman Bela. New Hampshire Insurance Department Final Report on 2014 Medical Cost Drivers tech. rep.Gorman Actuarial 2016.

[30] Harris Katherine M. How do patients choose physicians? Evidence from a national survey of enrollees in employment-related health plans *Health services research.* 2003;38:711–732.

[31] Tu Ha T., Lauer Johanna R.. Word of mouth and physician referrals still drive health care provider choice *Center for Studying Health System Change.* 2008:1–8.

[32] Baker Laurence C, Bundorf M Kate, Kessler Daniel P. Vertical integration: hospital ownership of physician practices is associated with higher prices and spending *Health Affairs.* 2014;33:756–763.

[33] Scott Kirstin W, Orav E John, Cutler David M, Jha Ashish K. Changes in hospital–physician affiliations in US hospitals and their effect on quality of care *Annals of Internal Medicine.* 2017;166:1–8.

[34] Lin Haizhen, McCarthy Ian M, Richards Michael. Hospital pricing following integration with physician practices *Journal of Health Economics.* 2021;77:102444.

[35] Carroll Caitlin, Chernew Michael, Fendrick A Mark, Thompson Joe, Rose Sherri. Effects of episode-based payment on health care spending and utilization: Evidence from perinatal care in Arkansas *Journal of health economics.* 2018;61:47–62.

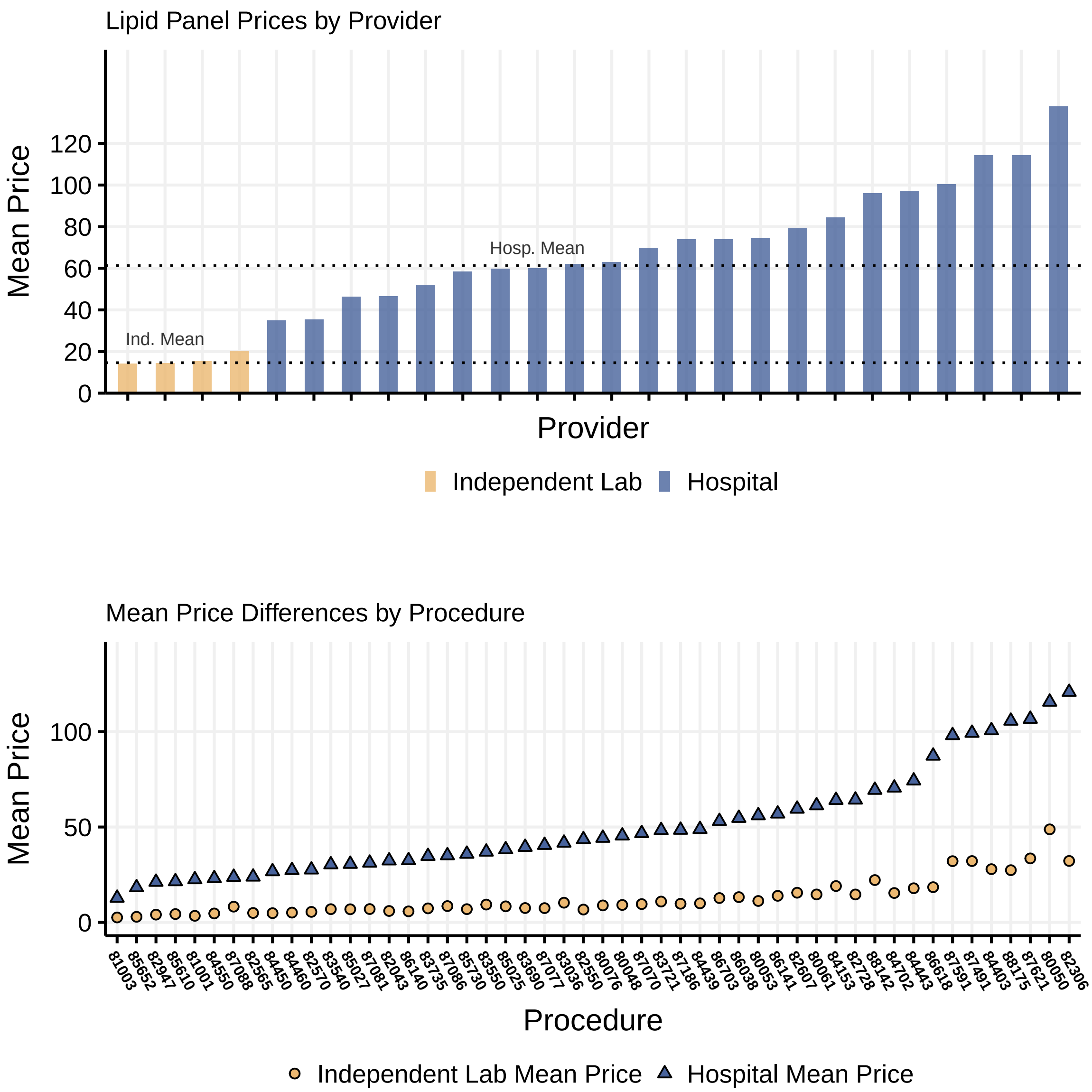
[36] Song Zirui, Ji Yunan, Safran Dana G, Chernew Michael E. Health care spending, utilization, and quality 8 years into global payment *New England Journal of Medicine.* 2019;381:252–263.

[37] Gowrisankaran Gautam, Nevo Aviv, Town Robert. Mergers when prices are negotiated: Evidence from the hospital industry *American Economic Review.* 2015;105:172–203.

[38] Robinson James C, Brown Timothy T. Increases in consumer cost sharing redirect patient volumes and reduce hospital prices for orthopedic surgery *Health Affairs.* 2013;32:1392–1397.

[39] Whaley Christopher M, Brown Timothy T. Firm responses to targeted consumer incentives: evidence from reference pricing for surgical services *Journal of Health Economics.* 2018;61:111–133.

Figure 1: Price Variation Across Providers



Notes: The top panel plots the average price paid for a lipid panel (CPT code 80061) at each lab provider in my primary sample. The horizontal dashed lines show the weighted average price all independent labs and all hospital-based labs, respectively. The bottom panel plots the weighted average hospital-based price and independent lab price for the 50 most common labs in the sample, which are labeled by their CPT/HCPCS codes.

Table 1: Price Differences and Available Savings

Test	Desc.	Hospital Price	Independent Lab Price	% Discount	Savings ($ Millions)	Savings/Person-Year
Aggregate		59.82	15.71	-73.73	-333.37	-253.32
80053	Comprehen metabolic panel	56.04	11.20	-80.01	-32.20	-24.47
85025	Complete cbc w/auto diff wbc	38.22	8.39	-78.06	-20.45	-15.54
80061	Lipid panel	61.27	14.62	-76.13	-26.94	-20.47
84443	Assay thyroid stim hormone	74.27	17.88	-75.92	-23.63	-17.96
83036	Glycosylated hemoglobin test	41.66	10.30	-75.28	-6.50	-4.94
82306	Vitamin d 25 hydroxy	120.74	32.21	-73.32	-16.52	-12.55
80048	Metabolic panel total ca	45.44	9.12	-79.93	-8.04	-6.11
87086	Urine culture/colony count	35.06	8.52	-75.69	-4.69	-3.56
81001	Urinalysis auto w/scope	22.49	3.42	-84.78	-3.11	-2.36
85610	Prothrombin time	21.46	4.35	-79.73	-3.06	-2.32

Notes: Columns 3 and 4 of this table report the weighted average hospital-based price and independent lab price, respectively, for the 10 most common labs in the sample and an aggregate measure. The weighted average for the aggregated price measure is computed as the weighted average across all tests and providers in that group. Column 5 of the table reports the independent lab discount in percentage terms. Column 6 reports the total savings available from reallocating labs from hospital-based providers to independent labs. The savings for each hospital-based lab is the difference between the total amount paid and the average non-hospital based price for that test. The total savings is then computed as the sum of savings over all hospital-based labs in the sample. The last column of the table reports the total savings divided by the number of unique person-years in the sample.

Table 2: Partial R^2 Estimates

	Likely Referring Provider		Patient Primary Care Provider	
Dependent Variable:	Independent Lab	Payment	Independent Lab	Payment
Independent Variable(s)				
Demographics	0.003	0.007	0.005	0.006
	(0)	(0.001)	(0)	(0)
Year	0.01	0.022	0.011	0.023
	(0)	(0.001)	(0)	(0)
Patient Zip	0.006	0.008	0.01	0.01
	(0)	(0)	(0)	(0)
Plan	0.022	0.03	0.025	0.028
	(0.001)	(0.001)	(0)	(0)
Provider ID	0.339	0.224	0.209	0.137
	(0.002)	(0.002)	(0.001)	(0.001)
Full Model R^2	0.467	0.523	0.376	0.459
Obs.	2,401,049	2,401,049	6,444,157	6,534,067

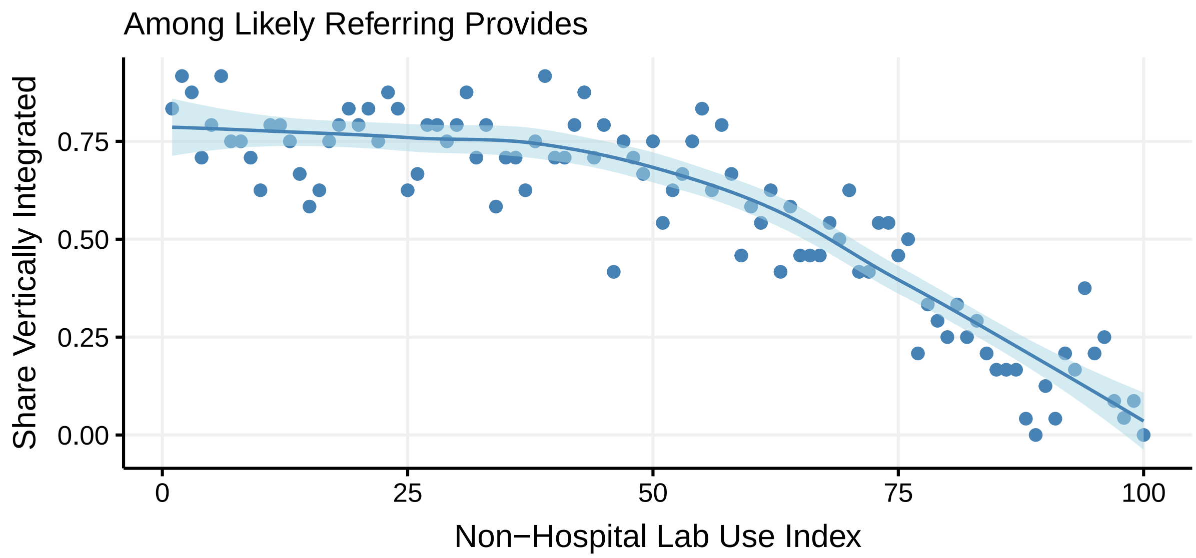
Notes: Table reports the partial R^2 estimates associated with regression model (1) in the text for each dependent variable group. In columns (1) and (2) the provider ID variable reflects the likely referrer ID and in columns 3 and 4 the provider ID reflects the patient's primary care physician (PCP). Likely referrers are defined, for each lab visit, as the primary care or specialist physician that the patient saw most recently before the lab test. PCPs are defined, for each patient, as the primary care physician the patient saw most frequently in a given year, and are assumed to remain constant over time unless a new PCP arises. The independent lab variable is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. The total payment for a particular lab is the sum of insurer payments and out-of-pocket costs associated with the service. Standard errors are computed using a bootstrap procedure with 1000 replications, and are reported in parentheses.

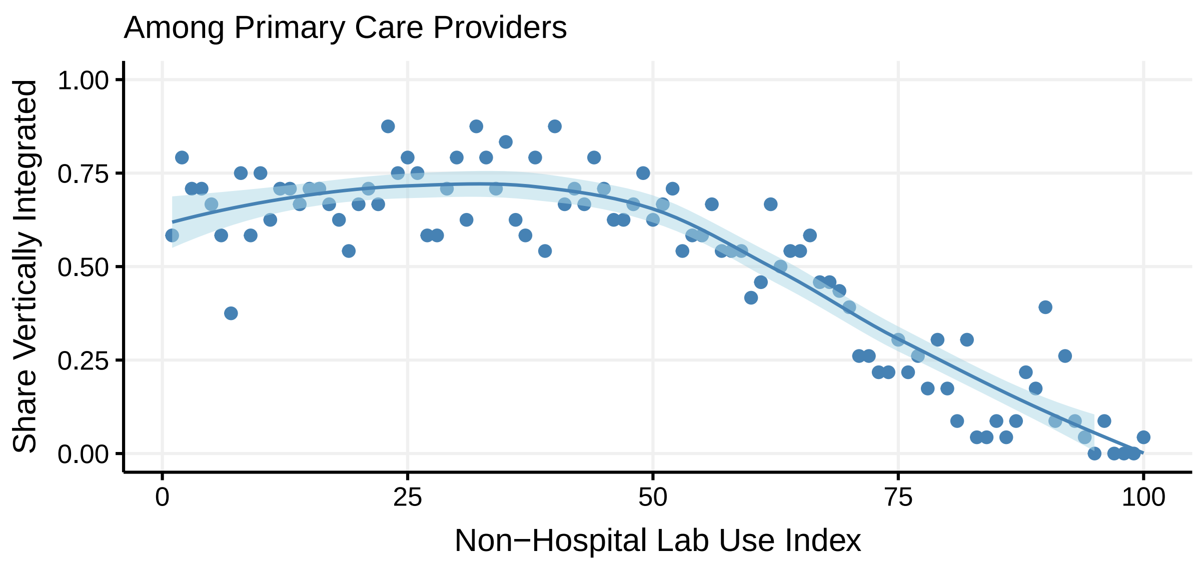
Table 3: Effects of Likely Referrers on Payments

Dependent Variables:	log(Total Payment)	Out-of-Pocket Payment	Independent Lab
	(1)	(2)	(3)
2nd quintile of NHUI	-0.033***	-0.010	0.016***
	(0.005)	(0.019)	(0.002)
3rd quintile of NHUI	-0.060***	-0.049*	0.042***
	(0.005)	(0.020)	(0.002)
4th quintile of NHUI	-0.104***	-0.136***	0.088***
	(0.006)	(0.024)	(0.003)
5th quintile of NHUI	-0.494***	-0.569***	0.363***
	(0.009)	(0.029)	(0.005)
Observations	1,472,038	791,340	1,472,038
R^2	0.70	0.45	0.70
Model	OLS	GLM log link	OLS

Notes: Table shows regression estimates associated with model (2) in the text. Each row reflects the estimated effect of having a likely referrer in the labelled quintile of the non-hospital use index (NHUI) distribution. The NHUI is defined, for each referrer, as the percentile transformation of their estimated fixed effect $\hat{\theta}^{prov}$ in the regression of independent lab use on the full sample of independent variables. In other words, the NHUI is a measure of the propensity with which likely referrers are associated with independent labs, adjusted for patient and plan characteristics. The model also includes year, month, procedure, and patient fixed effects. The model is estimated on the sample of patients who had lab visits across multiple likely referrers. The total payment for a particular lab is the sum of insurer payments and out-of-pocket costs associated with the service. The independent lab variable is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. Out-of-pocket costs reflect the total amount paid by the patient for the lab. The model for out-of-pocket costs is estimated as a GLM with a log link function to account for the presence of many zeros. Standard errors, clustered at the patient level, are reported in parentheses. ****: 0.001, **: 0.01, *: 0.05*

Figure 2: Non-Hospital-Based Lab Use and Vertical Integration





Notes: Top panel plots the share of likely-referring physicians who are vertically integrated for each percentile of the non-hospital use index (NHUI). The NHUI is defined, for each referrer, as the percentile transformation of their estimated fixed effect $\hat{\theta}^{prov}$ in the regression of independent lab use on the full sample of independent variables. In other words, the NHUI is a measure of the propensity with which likely referrers are associated with independent labs, adjusted for patient and plan characteristics. The bottom panel shows the analogous plot for patients' primary care physicians.

Table 4:

Dependent Variables:	log(Total Payment)	Out-of-Pocket Payment	Independent Lab
	(1)	(2)	(3)
Vertically Integrated	0.076***	0.126***	-0.062***
	(0.004)	(0.014)	(0.002)
Observations	1,472,038	1,472,038	1,472,038
R^2	0.70	0.45	0.67
Model	OLS	GLM log link	OLS

Notes: Table shows regression estimates associated with a modified version model (2) in the text, where the independent variable of interest is an indicator for vertical integration of the likely referrer. The model also includes year, month, procedure, and patient fixed effects. The model is estimated on the sample of patients who had lab visits across multiple likely referrers. The total payment for a particular lab is the sum of insurer payments and out-of-pocket costs associated with the service. The independent lab variable is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. Out-of-pocket costs reflect the total amount paid by the patient for the lab. The model for out-of-pocket costs is estimated as a GLM with a log link function to account for the presence of many zeros. Standard errors, clustered at the patient level, are reported in parentheses. ****: 0.001, **: 0.01, *: 0.05*

Appendix: Additional Tables and Figures

6 Additional Details on Sample Construction

To construct my main lab sample, I use the Restructured BETOS Classification System (RBCS) from CMS to identify all procedure codes in the subcategories of general laboratory, anatomic pathology, and molecular testing. I then compute, for each procedure, the share of total volume that occurs at hospital-based and non-hospital-based facilities. I drop procedures where either share exceeds 99%. To construct the sample used for the ANOVA analyses, I further restrict to procedures in the RBCS families blood count and clinical chemistry as these are the most common groups. I also drop urinalysis and cytopathology procedures. The resulting sample contains 97 distinct CPT/HCPCS codes, which are listed in Table A6. In robustness tests, I find that the main results are not sensitive to the construction of this subsample.

To construct the likely referrer and PCP samples, I first identify all E&M visits associated with each patient using CPT/HCPCS codes 99201, 99202, 99203, 99204, 99205, 99211, 99212, 99213, 99214, and 99215. I define a visit as a patient-day which includes at least one E&M code. I define the primary provider for each visit as the physician responsible for the most claims, or, in the event of a tie, the most payments. I use provider NPIs to link speciality information. I define PCPs as those having a speciality of family practice, internal medicine, general practice, pediatric medicine, physician assistant, or nurse practitioner. I keep specialist physicians in the following specialties: allergy / immunology, cardiology, endocrinology, hematology/oncology, obstetrics/gynecology, otolaryngology, rheumatology, and urology.

For each lab visit, I identify E&M visits with either a PCP or specialist that occur in the 30-day window preceding the lab, including the day of the lab. I define the likely referrer as the physician associated with the visit that occurs in closest proximity to the lab. The final likely-referrer-matched sample includes all lab test with a matching likely referrer.

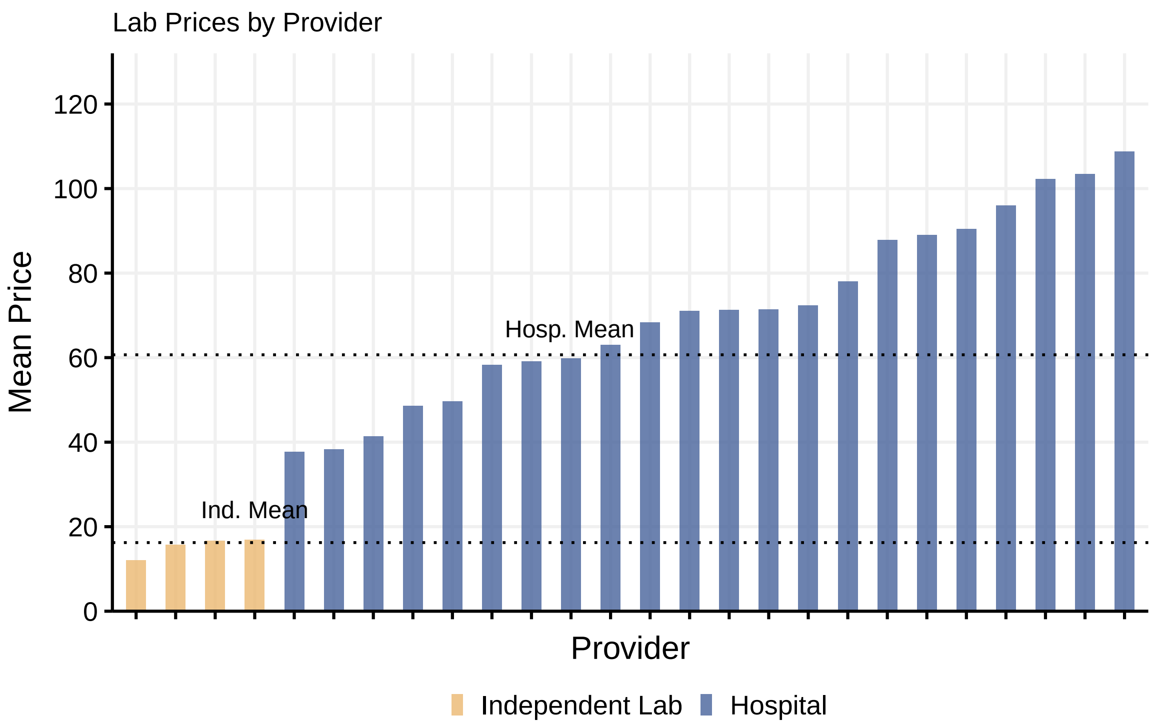
For each patient-year, I define the PCP as the primary care physician responsible for the most E&M visits in that year. For patient-years without any primary care visits, I use the most recent PCP identifier associated with that patient. I use E&M visits from 2005-2015 to identify PCPs. The final PCP-matched sample includes all labs with a matching PCP.

Table A1: Summary Statistics of Estimation Samples

	Likely-Referrer Sample		Primary Care Provider Sample	
	Mean	Sd	Mean	Sd
Total Payments	42.65	51.88	43.85	48.53
Out-of-Pocket	7.57	22.05	7.75	22.64
Insurer Payment	35.08	51.30	36.10	47.99
Non-Hospital	0.20	0.40	0.21	0.41
Anthem	0.52	0.50	0.53	0.50
Harvard Pilgrim	0.22	0.42	0.22	0.41
Cigna	0.26	0.44	0.26	0.44
Count	2,418,233		6,534,067	

Notes: Table reports summary statistics on the two main lab samples used in the regression analyses. The likely-referrer sample includes labs that were able to be linked to a likely-referrer within the 30-day window prior to the lab visit. The primary care provider sample includes labs that were able to be linked to a patient with an identifiable primary care provider over the sample period.

Figure A1: Price Index Variation Across Providers



Notes: Figure depicts the weighted average lab price across the 25 most common labs in the sample for all hospital-based labs and independent providers. Weights are based on the procedure-level aggregate volume shares. The horizontal dashed lines show the weighted average price all independent labs and all hospital-based labs, respectively.

Table A2: Partial R^2 Estimates Using Alternative Specifications

	Most Recent Provider		Non-same-day Provider		Most Common Provider	
Dependent Variable:	Independent Lab	Payment	Independent Lab	Payment	Independent Lab	Payment
Independent Variable(s)						
Demographics	0.003	0.006	0.003	0.004	0.004	0.006
se Demographics	(0)	(0)	(0)	(0.001)	(0)	(0)
Year	0.011	0.023	0.013	0.023	0.011	0.022
se Year	(0)	(0.001)	(0)	(0)	(0)	(0.001)
se Procedure	(0)	(0.004)	(0)	(0.003)	(0.001)	(0.002)
Patient Zip	0.008	0.009	0.012	0.013	0.008	0.009
se Patient Zip	(0.001)	(0.001)	(0)	(0)	(0)	(0.001)
Plan	0.025	0.03	0.033	0.033	0.025	0.03
se Plan	(0.001)	(0.001)	(0.002)	(0)	(0)	(0.001)
Provider ID	0.285	0.193	0.183	0.129	0.274	0.185
se Provider ID	(0.001)	(0.002)	(0)	(0)	(0.002)	(0.001)
Full Model R^2	0.423	0.501	0.343	0.461	0.413	0.496
Obs.	3,372,258	3,372,258	2,350,625	2,350,625	3,372,258	3,372,258

Notes: Table reports the partial R^2 estimates associated with regression model (1) in the text for each dependent variable group and three alternative specifications from those presented in Table 2. For the first two columns the provider ID reflects the likely referrer identified using a 90 day lookback window. For columns 3 and 4, I drop labs that occur on the same day as the likely-referring E&M visit. For columns and 6, I define the likely referrer as the most common primary care or specialist seen in the 90 day period before the lab. The independent lab variable is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. The total payment for a particular lab is the sum of insurer payments and out-of-pocket costs associated with the service. Standard errors are computed using a bootstrap procedure with 1000 replications, and are reported in parentheses.

Table A3: Iterative Inclusion of Independent Variables: Likely Referrer Linear Model

Dependent Variable:			Independent Lab		
	(1)	(2)	(3)	(4)	(5)
Age	0.0006***	0.0006***	0.0008***	0.0009***	0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00009)
Female	-0.008	-0.008	-0.009	-0.010*	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)
Charlson	-0.019***	-0.018***	-0.018***	-0.018***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0006)
Procedure	Yes	Yes	Yes	Yes	Yes
Patient Zip			Yes	Yes	Yes
Plan				Yes	Yes
Likely Referrer					Yes
Observations	2,401,049	2,401,049	2,401,049	2,401,049	2,401,049
R^2	0.06	0.06	0.18	0.19	0.47

Notes: Table reports the results from 5 different regression specifications, where an additional independent variable is added each time. The dependent variable is an indicator that is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. Values "yes" in the last 4 rows of the table indicate inclusion of the associated factor in the regression. Standard errors, clustered at the patient level, are reported in parentheses. ****: 0.001, **: 0.01, *: 0.05*

Table A4: Iterative Inclusion of Independent Variables: Likely Referrer Logit Model

Dependent Variable:	Independent Lab				
	(1)	(2)	(3)	(4)	(5)
Age	0.0006***	0.0006***	0.0008***	0.0009***	0.0009***
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.00009)
Female	-0.008	-0.008	-0.009	-0.010*	-0.004
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)
Charlson	-0.019***	-0.018***	-0.018***	-0.018***	-0.009***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0006)
Procedure	Yes	Yes	Yes	Yes	Yes
Patient Zip			Yes	Yes	Yes
Plan				Yes	Yes
Likely Referrer					Yes
Observations	2,401,049	2,401,049	2,401,049	2,401,049	2,401,049
R^2	0.06	0.06	0.18	0.19	0.47

Notes: Table reports the results from 5 different regression specifications, where an additional independent variable is added each time. The dependent variable is an indicator that is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. All models are estimated as logit GLMs. Values ”yes” in the last 4 rows of the table indicate inclusion of the associated factor in the regression. Standard errors, clustered at the patient level, are reported in parentheses. ****: 0.001, **: 0.01, *: 0.05*

Table A5: Iterative Inclusion of Independent Variables: PCP Linear Model

Dependent Variable:	Independent Lab				
	(1)	(2)	(3)	(4)	(5)
Age	0.0008***	0.0008***	0.001***	0.001***	0.001***
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Female	-0.0004	-0.0004	-0.003	-0.003	-0.006
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)
Charlson	-0.018***	-0.018***	-0.018***	-0.018***	-0.014***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.0010)
Procedure	Yes	Yes	Yes	Yes	Yes
Patient Zip			Yes	Yes	Yes
Plan				Yes	Yes
Likely Referrer					Yes
Observations	6,444,157	6,444,157	6,444,157	6,444,157	6,444,157
R^2	0.05	0.06	0.18	0.20	0.37

Notes: Table reports the results from 5 different regression specifications, where an additional independent variable is added each time. The dependent variable is an indicator that is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. All models are estimated as logit GLMs. Values "yes" in the last 4 rows of the table indicate inclusion of the associated factor in the regression. Standard errors, clustered at the patient level, are reported in parentheses. ****: 0.001, **: 0.01, *: 0.05*

Table A6: Iterative Inclusion of Independent Variables: PCP Logit Model

Dependent Variable:	Independent Lab				
	(1)	(2)	(3)	(4)	(5)
Age	0.005***	0.005***	0.008***	0.009***	0.012***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Female	-3.43×10^{-6}	0.0004	-0.019	-0.021	-0.050
	(0.035)	(0.035)	(0.037)	(0.037)	(0.037)
Charlson	-0.154***	-0.152***	-0.167***	-0.166***	-0.165***
	(0.014)	(0.014)	(0.015)	(0.016)	(0.017)
Procedure	Yes	Yes	Yes	Yes	Yes
Patient Zip			Yes	Yes	Yes
Plan				Yes	Yes
Likely Referrer					Yes
Observations	6,444,157	6,444,157	6,444,086	6,444,086	6,393,054
Pseudo R^2	0.05	0.06	0.17	0.19	0.35

Notes: Table reports the results from 5 different regression specifications, where an additional independent variable is added each time. The dependent variable is an indicator that is equal to 1 if the lab is performed at a non-hospital-based facility and 0 otherwise. All models are estimated as logit GLMs. Values "yes" in the last 4 rows of the table indicate inclusion of the associated factor in the regression. Standard errors, clustered at the patient level, are reported in parentheses. ****: 0.001, **: 0.01, *: 0.05*

Table A7: Summary of Main Lab Procedures

CPT/HCPCS	Description	Mean Price	SD Price	Count
80053	Comprehen metabolic panel	48.72	37.08	858,033
85025	Complete cbc w/auto diff wbc	34.43	21.59	785,529
80061	Lipid panel	48.94	32.89	785,133
84443	Assay thyroid stim hormone	64.06	34.11	511,690
83036	Glycosylated hemoglobin test	33.86	20.87	275,877
82306	Vitamin d 25 hydroxy	93.97	67.52	267,473
80048	Metabolic panel total ca	40.70	65.34	254,622
85610	Prothrombin time	19.26	73.28	205,026
85027	Complete cbc automated	27.21	83.70	196,871
84153	Assay of psa total	50.05	31.00	151,600
80050	General health panel	76.78	74.85	132,601
84439	Assay of free thyroxine	38.65	28.26	130,159
80076	Hepatic function panel	37.54	30.00	125,795
85652	Rbc sed rate automated	14.06	14.15	93,210
82043	Microalbumin quantitative	26.14	24.82	79,656
82728	Assay of ferritin	52.72	33.74	76,798
82607	Vitamin B-12	45.41	30.12	75,612
83690	Assay of lipase	37.03	20.31	75,580
82947	Assay glucose blood quant	18.50	16.50	74,709
82550	Assay of ck (cpk)	37.94	29.84	70,279
82565	Assay of creatinine	21.25	124.64	66,332
84460	Alanine amino (ALT) (SGPT)	22.71	16.83	66,331
83540	Assay of iron	24.74	17.03	62,774
83735	Assay of magnesium	30.83	24.82	61,848
86140	C-reactive protein	26.24	20.97	61,179
82570	Assay of urine creatinine	20.15	15.55	57,269
84550	Assay of blood/uric acid	17.94	17.24	49,552
83550	Iron binding test	30.24	19.21	49,131
84450	Transferase (AST) (SGOT)	22.17	15.51	49,065
85730	Thromboplastin time partial	33.38	24.20	46,953
84403	Assay of total testosterone	78.41	52.48	46,252
84702	Chorionic gonadotropin test	61.02	42.82	43,222
86141	C-reactive protein hs	47.13	27.26	38,568
82746	Assay of folic acid serum	46.55	31.66	38,297
85651	Rbc sed rate nonautomated	20.03	12.58	37,816
84520	Assay of urea nitrogen	18.35	50.87	36,095
84436	Assay of total thyroxine	25.13	20.86	35,787
84703	Chorionic gonadotropin assay	47.77	158.92	32,506
85018	Hemoglobin	12.36	10.74	30,783
84100	Assay of phosphorus	19.70	17.56	28,824
85014	Hematocrit	11.20	9.15	28,787
82150	Assay of amylase	34.95	24.15	28,543
84481	Free assay (FT-3)	54.29	42.58	27,563
83001	Assay of gonadotropin (fsh)	62.78	40.44	26,213
83615	Lactate (LD) (LDH) enzyme	22.63	14.93	24,594
82248	Bilirubin direct	17.18	16.31	21,856
83970	Assay of parathormone	132.12	89.66	21,221
81015	Microscopic exam of urine	13.27	7.86	20,950
84402	Assay of free testosterone	74.72	52.58	20,277
84480	Assay triiodothyronine (t3)	49.73	34.82	19,633

Table A8: Summary of Main Lab Procedures

CPT/HCPCS	Description	Mean Price	SD Price	Count
80051	Electrolyte panel	34.77	62.09	18,912
84479	Assay of thyroid (t3 or t4)	19.40	18.24	18,313
84146	Assay of prolactin	68.09	46.12	17,961
82670	Assay of estradiol	90.66	59.30	17,286
83002	Assay of gonadotropin (lh)	62.10	39.98	17,003
80055	Obstetric panel	130.76	94.59	15,776
82950	Glucose test	17.85	14.98	15,404
82465	Assay bld/serum cholesterol	20.26	14.45	15,252
84156	Assay of protein urine	21.55	21.90	15,000
83655	Assay of lead	38.98	25.20	14,001
84132	Assay of serum potassium	22.58	119.11	13,671
82105	Alpha-fetoprotein serum	54.81	37.33	13,499
82310	Assay of calcium	20.49	52.24	12,939
84165	Protein e-phoresis serum	46.46	29.91	12,387
82040	Assay of serum albumin	18.65	13.53	12,378
84478	Assay of triglycerides	22.09	15.53	11,576
82652	Vit d 1 25-dihydroxy	117.13	71.38	10,680
82977	Assay of GGT	26.57	19.83	10,654
80074	Acute hepatitis panel	136.52	99.75	10,253
82247	Bilirubin total	21.78	13.50	10,174
84144	Assay of progesterone	65.59	42.59	9,791
84155	Assay of protein serum	16.61	15.08	9,544
80069	Renal function panel	36.64	36.47	9,066
82533	Total cortisol	61.55	50.21	8,379
83090	Assay of homocystine	55.85	51.42	7,935
80197	Assay of tacrolimus	49.54	55.47	7,803
84154	Assay of psa free	49.75	36.40	7,599
83525	Assay of insulin	38.41	37.85	7,578
82378	Carcinoembryonic antigen	78.28	52.62	7,500
84075	Assay alkaline phosphatase	19.65	14.69	7,404
83718	Assay of lipoprotein	35.47	17.84	6,761
82627	Dehydroepiandrosterone	62.51	51.49	6,666
84466	Assay of transferrin	55.55	26.19	6,199
82951	Glucose tolerance test (GTT)	52.82	35.72	6,029
80178	Assay of lithium	31.13	23.38	5,917
84270	Assay of sex hormone globul	44.78	31.28	5,694
84163	Pappa serum	51.33	29.56	5,672
80164	Assay dipropylacetic acid	55.52	35.74	5,584
89051	Body fluid cell count	45.18	49.98	5,008
82677	Assay of estriol	58.04	48.17	4,819
84425	Assay of vitamin b-1	69.49	53.66	4,633
83921	Organic acid single quant	60.41	47.85	4,534
82340	Assay of calcium in urine	24.91	18.91	4,340
83883	Assay nephelometry not spec	91.49	77.08	4,335
84134	Assay of prealbumin	52.14	28.62	4,322
85045	Automated reticulocyte count	17.37	14.93	4,246
85048	Automated leukocyte count	8.52	9.35	3,887