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Do Physicians' Financial Incentives Affect Medical Treatment and Patient Health?

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Abstract

We investigate whether physicians' financial incentives influence health care supply, technology diffusion, and resulting patient outcomes. In 1997, Medicare consolidated the geographic regions across which it adjusts physician payments, generating area-specific price shocks. Areas with higher payment shocks experience significant increases in health care supply. On average, a 2 percent increase in payment rates leads to a 5 percent increase in care provision. Elective procedures such as cataract surgery respond twice as strongly as less discretionary services. Higher reimbursements increase the pace of technology diffusion, as non-radiologists acquire MRI scanners when prices increase. Incremental care has no impacts on patient health.

Critics have charged that fee-for-service medicine leads to high medical expenditures without improving patient health.[1] Alternatively, the incentives embedded in volume-based compensation may facilitate access to valuable treatments (Ellis and McGuire, 1986).[2] Determining the fiscal consequences of volume-based payment policies and the health benefits of incremental care are thus pressing empirical tasks (Baicker and Chandra, 2011).

We study how changes in physicians' financial incentives influence the quantity, composition, and value of health care they provide. Since payment policies may influence medical innovation through their effect on technology adoption (Weisbrod, 1991; Chandra and Skinner, 2011), we also examine their impact on physician investment decisions. Finally, we investigate the consequences of incremental treatments and technologies for patient health, the crucial outcome for any intervention in health care financing and delivery.

We estimate the effects of payment rates using an overhaul of geographic adjustments to provider reimbursements in the Medicare program. In 1997, Medicare consolidated the areas across which it adjusts physician payments, reducing the number of payment regions nationally from 210 to 89. This consolidation led to area-specific price shocks that are plausibly exogenous with respect to other changes in local health care demand and supply. We use these payment changes to estimate the effect of prices on care provision, technology diffusion, and patient health.

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[1]For instance, see Arrow et al. (2009), Ginsburg (2011), and Hackbarth et al., (2008).

[2]The care physicians provide has personal financial consequences, as 60 percent are self-employed (Wassenaar and Thran, 2003, Table 2) and 85 percent of those in group practices have compensation linked to patient care revenues (Medical Group Management Association, 1998, Table 12).

We find that physician and outpatient care follows a traditional positively-sloped supply curve. Health care supply exhibits a long-run elasticity of around 2.5 with respect to reimbursement rates. The response is twice as large for relatively elective procedures, including cataract removal and colonoscopy, as for less discretionary services, such as oncological procedures and dialysis. Theory predicts exactly this pattern; when physicians value patient health, services with a clear benefit for some patients, and none for others, should respond less to payment rates.[3]

Reimbursement rate increases lead physicians to adjust treatment patterns along several margins. More providers serve Medicare patients and those who do adjust both the quantity and composition of services they supply. The responses unfold over several years, suggesting that changes in profitability induce dynamic changes in physician practice.

One such adjustment consists of investment in new technology. We investigate the vertical integration of office visits and imaging services that occurs when non-radiologists invest in magnetic resonance scanners. Reimbursement rates influence these investment decisions and hence the diffusion of medical technology. Just as Acemoglu and Finkelstein (2008) observe in the context of hospitals, we find that Medicare's payment policies spur physicians' technological investments. These investments increase doctors' profit margins and medical spending.

Patients with cardiovascular disease face significant potential gains from

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[3]Our result runs counter to assumptions embodied in the federal budgeting process, which assumes a 30 to 50 percent "volume offset," or negative supply response (Congressional Budget Office, 2007; Codespote, London and Shatto, 1998), due to backward-bending labor supply (Gruber and Owings, 1996; Rice, 1983).

medical treatments, as new technologies like cardiac catheterization have expanded treatment options. They also have much at risk since heart disease is the leading cause of mortality in the United States (Cutler, 2004; Murphy and Topel, 2006). Consistent with our aggregate results, we find that price increases significantly expand the supply of services to these patients, with an overall price elasticity of 1.2.

For both the patients with cardiovascular disease and the broader Medicare population we find little impact of incremental care on either mortality or health status. Among the overall Medicare population, we are able to rule out mortality reductions that would be cost effective at conventional values of extending life. For patients with cardiovascular disease, incremental care has insignificant effects on the occurrence of hospitalizations, heart attacks, and mortality. If anything, incremental outpatient care is positively associated with hospital expenditures.

These results are consistent with the RAND Health Insurance Experiment's demand-side finding that care induced by reductions in patient cost-sharing has little impact on health (Manning et al., 1987). But they contrast with those of Chandra, Gruber and McKnight (2010), who find that preventative care reduces subsequent hospital expenditures. The broader packages of outpatient care we study appear not to substitute for inpatient care in this way.

Physicians' substantial responses to price changes suggest that payment rates play an important role in driving medical care consumption. While extrapolation to other time periods is naturally imperfect, we estimate that increases in profitability can explain up to one third of the growth in spending

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on outpatient care since 1982. Together with changes in patient cost sharing (Finkelstein, 2007) and increases in the demand for health (Hall and Jones, 2007), providers' financial incentives appear to have played an important role in expanding the health care sector.

1   Reimbursement Rates, Physician Practice Styles, and the Supply of Health Services

Physicians face major decisions about the organization of their practices and the quantities of care they provide. A variety of investments in capital and skills can shift physicians, and by extension their patients, into more and less intense treatment regimes. Orthopedists can acquire advanced imaging equipment, urologists can invest in radiation therapy units, and cardiologists can integrate nuclear stress testing into their practices.[4] These arrangements involve up-front investments that increase profit margins going forward. We integrate these investment decisions, and their implications for the development of new health care technologies, into a model of medical treatment under administered prices.

1.1   Medical Care Supply

Physicians can practice medicine using a standard practice style (S) that has a variable cost of $\bar{c}$ per unit of care, or an intense practice style (I) that reduces unit costs to $\underline{c}$ but costs $k > 0$ to adopt. For instance, acquiring a

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[4]Affendulis and Kessler (2007) and Shah et al. (2011) show that vertically integrated cardiology practices influence patients' treatment courses, as does Baker (2010) for self-referral to magnetic resonance imaging.

computed tomography (CT) scanner allows the practice to generate revenue with low marginal costs and minimal use of the doctors' valuable time.

Because insurance diminishes or eliminates price sensitivity (Feldstein, 1973) and consumers lack information about treatment options, physicians make many health care decisions on their patients' behalf (Arrow, 1963). We assume that demand is unsatiated, so that physicians' supply decisions drive the quantity of health care their patients receive.[5] Since physicians act, at least in part, as agents on each patient's behalf, the patient's benefit curve influences supply decisions.[6] Using Q to denote the market's aggregate supply, we let $b(Q)$ capture the health benefit of marginal care. This benefit enters directly into the physician's utility function. Marginal benefits are decreasing in Q and individual physicians take $b(Q)$ as given.

A continuum of physicians has productivity γ_i distributed over $(0, \infty)$ according to $F(\cdot)$, already known when they make investment decisions. Doctor i takes $1/\gamma_i$ units of time to produce one unit of care. Each must choose a technology, S or I, and quantity of care, q. Public health insurance programs compensate providers for this care according to administratively set payments at reimbursement rate r per unit of care, as opposed to competitively set prices (Newhouse, 2003). With quasilinear utility in income, utility in the standard

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[5]While traditional Medicare does have co-payments, 90 percent of beneficiaries have either supplemental insurance or are eligible for a state-funded Medicaid supplemental that reduces or eliminates patient costs at the margin (Medicare Payment Advisory Commission, 2011).

[6]This contrasts with standard markets in which the benefit curve would simply describe demand.

and intense practice regimes is:[7]

$$
\begin{aligned}
U_S(q; \gamma_i) &= (r - \bar{c})q - e\left(\frac{q}{\gamma_i}\right) + \alpha b(Q)q \\
U_I(q; \gamma_i) &= (r - \underline{c})q - k - e\left(\frac{q}{\gamma_i}\right) + \alpha b(Q)q,
\end{aligned} \tag{1}
$$

where e is an increasing and convex function of physician time that captures decreasing returns to leisure.[8] The last term captures physicians' desire to provide beneficial care. This agency benefit is linear in the value of care, the amount supplied, and the weight placed on patient benefits. Proposition 1 defines physicians' utility maximizing investment and service-supply decisions.

Proposition 1 *There exists a threshold productivity γ^* such that physicians invest if and only if $\gamma > \gamma^*$. The threshold decreases in the reimbursement rate r and in the weight placed on patient benefits α. Aggregate supply increases in the reimbursement rate, with a slope given by*

$$
\frac{dQ}{dr} = \underbrace{\int_0^{\gamma^*(r)} \frac{dq_S^*(\gamma)}{dr} f(\gamma)d\gamma}_{\text{Standard practice style}} + \underbrace{\int_{\gamma^*(r)}^{\infty} \frac{dq_I^*(\gamma)}{dr} f(\gamma)d\gamma}_{\text{Intensive practice style}}
$$
$$
\underbrace{- \frac{d\gamma^*}{dr} f(\gamma^*)\left[q_I^*(\gamma^*) - q_S^*(\gamma^*)\right]}_{\text{Physicians switching practice styles}}. \tag{2}
$$

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[7]This treatment of income, which implies high-powered financial incentives, applies quite directly to the three-fifths of American physicians that are self-employed (self-employment data are available in Wassenaar and Thran, 2003, Table 2). It is also a reasonable approximation of the incentives faced by the 85 percent of physicians in group practices who, as of 1997, had their compensation directly linked to revenue (Medical Group Management Association, 1998, Table 12).

The quasilinear utility assumption simplifies the analysis and predicts positive supply responses, which are borne out in our empirical work.

[8]We assume that $e(\cdot)$ satisfies $e(0) = 0, e'(0) = 0, e'(\cdot) > 0, e''(\cdot) > 0$.

The equilibrium described in Proposition 1, which is proven in Appendix A, involves two classes of physicians. At a given reimbursement rate, firms above the productivity threshold γ^* invest and have higher optimal production levels than firms with $\gamma < \gamma^*$, who do not invest. The more productive firms are shown on the right in Figure 1, and the vertical part of the solid line depicts the investment threshold γ^*.

The supply response described by equation (2) is composed of three parts, corresponding to the three regions of the figure. The first term, which integrates over the lower part of the effort cost distribution, captures the supply shift from firms that do not invest at either reimbursement rate. The second term captures a similar continuous shift from firms that invest at either price. The "practice style effect" drives some firms to invest only after the reimbursement rate increases, illustrated by the the shift in the vertical line. These firms expand supply quantity dramatically after the return to investing increases. The magnitude of this effect depends on the density of firms near the investment threshold (Caballero and Engel, 1999), and is likely to be larger following a period of high uncertainty (Bloom, Bond and Van Reenen, 2007),

1.2   Health Care Supply and Patient Welfare

Welfare in this market depends directly on patient health benefits. Physicians supply care up to the point where their profit margins equal effort cost less their agency benefit from improved patient health. When physicians value health gains ($\alpha > 0$), supply responds less strongly to prices than it would on the basis of financial motives alone. Supply responses are particularly small

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when health benefits diminish rapidly as the market moves down the marginal benefit curve ($b'(Q)$ is very negative).[9] This is likely true with emergency care, which has high benefits for a small fraction of the population and no benefit for the remainder, and treatments such as chemotherapy, which has significant side effects and is only worthwhile for cancer patients. In contrast, elective procedures like cataract surgery offer modest or moderate benefits for large swaths of the population, implying flatter marginal benefit curves ($b'(Q)$ is small) and hence relatively large supply elasticities.

The quantity is only optimal when the social benefits of marginal care equal its cost. Physicians' optimization ensures that marginal costs equal the reimbursement rate. The equilibrium is thus socially efficient when $r = b(Q^*)$, which only holds if payments are set optimally. A sufficient statistic for the welfare impact of price changes is:

$$\frac{dW}{dr} = [b(Q) - r]\frac{dQ}{dr}.$$

Higher reimbursements reduce welfare when prices r exceed marginal health benefits $b(Q)$. While we can directly measure r using Medicare's reimbursement rates, the supply response and health impacts must be estimated using an exogenous source of price variation. We employ a previously unexploited natural experiment for this task.

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[9]Holding practice style fixed, a given physician's physician's supply response to reimbursement rates is $\frac{dq^*}{dr} = \left[1 + \alpha b'(Q)\frac{dQ}{dr}\right]\frac{\gamma_i^2}{e''(q/\gamma_i)}$. With a more general utility function in income, supply responses would depend on the relative magnitudes of substitution effects (Staiger, Auerbach and Buerhaus, 2010) and income effects (Gruber and Owings, 1996; Congressional Budget Office, 2007).

2 Price Shock From 1997 Payment Area Consolidation

We estimate the influence of price shocks on health care provision, technological diffusion, and health outcomes in the context of Medicare Part B, which finances outpatient care for most elderly Americans.[10] Since 1992, Medicare has paid physicians and other outpatient providers through a system of centrally administered prices, based on a national fee schedule. While the fee schedule assigns a fixed "relative value" (a quantity metric) to each health care service,[11] it recognizes that goods and services have different production costs in different parts of the country. For service j, supplied by a provider in payment area a, the provider's fee is approximately:[12]

$$\text{Reimbursement}_{a(i),j,t} = \text{Conversion Factor}_t \times \text{Relative Value Units}_j$$
$$\times \text{Geographic Adjustment Factor}_{a(i)}. \tag{3}$$

The Conversion Factor is a national adjustment factor, updated annually and generally identical across all services; it was equal to \$37.8975 in 2005.[13] The Relative Value Units (RVUs) associated with service j are intended to measure

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[10]Medicare covers nearly every American over age 65, and some additional beneficiaries eligible due to end-stage renal disease or disability. We study only those over 65. According to the Centers for Medicare and Medicaid Services, at `https://www.cms.gov/MedicareMedicaidStatSupp/downloads/05SS_CostShare_z.zip` (Table 19a; accessed October 16, 2011), beneficiaries' cost sharing was 15.6 percent of total spending as of 2003, including that part paid by private supplemental insurance.

[11]These values are determined according to the Resource-Based Relative Value Scale (RBRVS), initially developed by Hsiao et al. (1988).

[12]This is a slight simplification; Appendix B.1 details the payment structure.

[13]The annual political wrangling over the "doc fix" results from the statutory formula, known as the Sustainable Growth Rate, that drives the evolution of the Conversion Factor.

the resources required to provide that service. RVUs are constant across areas while varying across services. Finally, the Geographic Adjustment Factor (GAF) is the federal government's adjustment for differences in input costs across payment regions. The adjustments are derived from Census and other data on area-level rents, wages, and malpractice insurance premiums. Reimbursements for physicians in county i depend on the beneficiary-weighted average of input costs across all counties in payment area $a(i)$.[14]

We estimate the influence of prices on health care supply using changes induced by an administrative shift in the system of geographic adjustments. In 1997, the Health Care Financing Administration consolidated the payment regions in many states, leading to reimbursement rate shocks that vary across the pre-consolidation regions. The 210 payment areas that existed as of 1996 were consolidated to 89 distinct regions, as shown in Figure 2. The top panel of Figure 2 presents the regions as of 1996, with darker colors indicating higher GAFs; the middle panel shows the post-consolidation payment regions. As the maps indicate, the consolidation of payment regions dramatically changed the county groupings in many states, leading to differential price shocks. We estimate the responses of medical care supply, technology adoption, and patient welfare to these shocks.[15]

A comparison of these two maps, summarized in the third panel, reveals several key features of the payment area consolidation. First, substantial vari-

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[14]By exploiting cross-sectional differences between costs in county i and broader area $a(i)$, Hadley et al. (2009) estimate supply responses for ten services consistent with our results.

[15]Geographic adjustments to hospital reimbursements under Medicare Part A are structured differently from the physician and outpatient reimbursements discussed here, so were not affected by this consolidation.

ation in reimbursement rates was eliminated in many states. Wisconsin, Kentucky, Alabama, and other states were collapsed from many regions to a single statewide payment area. The number of regions was also reduced substantially in large states like Texas and California. Second, increases in reimbursement rates generally took place in rural areas while decreases took place in urban areas, as shown in Appendix Figure E.1. We address the possibility of differential trends across these areas by flexibly controlling for time-varying rural-urban differences, by directly controlling for a time trend in the price shock, and by restricting our sample to those counties that pass a matching criterion.

2.1 Empirical Specification

Using the price changes discussed above, we estimate the effect of reimbursements on care provision with specifications of the following form:

$$\ln(\text{RVUs}_{i,s(i),t}) = \sum_{t \neq 1996} \beta_t \cdot \text{Price Change}_i \times I_t$$
$$+ \gamma_i + \delta_t + \eta_{s(i),t} + \zeta' X_{i,s(i),t} + \varepsilon_{i,s(i),t}. \tag{4}$$

Our most comprehensive measure of health care supply is the log of total RVUs provided per patient seen in county i in state $s(i)$ during year t. We later decompose care across provider and service types as well as by service quantity and intensity.

In our baseline analysis, we estimate equation (4) on data aggregated to the county-by-year level. We interact our price shocks, Price Change$_i$, with an indicator I_t for observations in year t. We exclude the interaction for 1996,

so 1996 is the base year relative to which each β_t is estimated. Estimates of β_t for years prior to 1996 provide a sense for the importance of pre-existing trends that are correlated with Price Change$_i$, while estimates of β_t for years following 1996 measure the effect of reimbursement rates on care provision. Since the quantity of RVUs per beneficiary is expressed in logs and the GAF is an index normalized to a mean of 1, these β_t coefficients can be interpreted as elasticities. We denote county fixed effects by γ_i, year fixed effects by δ_t, and state-by-year effects by $\eta_{s(i),t}$. These fixed effects capture the effects of other changes to payment policies and the structure of medical care that took place during this time period, which we discuss in Appendix B.2.

We control for county characteristics $X_{i,s(i),t}$ that are either correlated with the consolidation-induced GAF changes or may be important determinants of care per Medicare beneficiary. Most importantly, price increases occurred primarily in rural areas while decreases occurred in urban areas. We thus allow for differential urban-rural trends by controlling for interactions between year indicator variables and the log of each county's 1990 population. We confirm that the baseline estimates are robust to controlling similarly for base year quantities of care, population density, and whether or not a county is located within a metropolitan statistical area. To reduce noise resulting from changes in the health of the beneficiaries sampled from small counties, we use standard controls for the fraction of each county's sample that meets particular health and demographic criteria.

Our baseline estimate of equation (4) uses a sample of counties that pass the following matching procedure. We first regress our price shocks on baseline

county characteristics using the sample of states in which payment locality consolidations occurred (the "affected" sample).[16] Using the results from this regression, we generate predicted price shocks for the full sample of counties, including those that are not in states that were affected by consolidations. The sample used in our baseline estimates includes all nearest-neighbor matches (matched on the predicted price shocks) between a county from the "affected" set of states and a county from the unaffected set.[17] We calculate standard errors under the assumption that the error term $\varepsilon_{i,s(i),t}$ is clustered at the level of pre-1997 payment areas.

2.2 Medicare Data

Our data on health care provision come from claims submitted by providers to Medicare for reimbursement. The data document all claims associated with a 5 percent random sample of the Medicare Part B beneficiary population for each year from 1993 through 2005.[18] The same individuals are sampled each year, and the data contain itemized reports of the services purchased for them by Medicare. We obtain demographic information about our beneficiary sample from the Denominator files, and summary statistics are in Table 1.

We compute the aggregate quantity of health care supplied to this sample of beneficiaries using the scaling of individual services that the Centers for

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[16]These characteristics are log population in 1990, log density in 1990, and level of the GAF in 1990.

[17]We show that our results are little affected by including the full sample of counties.

[18]Part B, formally known as Supplementary Medical Insurance, is the part of Medicare that covers physician services and outpatient care, including all of the fee schedule care we study. By including only beneficiaries participating in Part B, we are ignoring those recipients of Part A hospital insurance who choose not to enroll in Part B, as well as those who choose a Medicare Advantage managed care plan instead of traditional Part B.

Medicare and Medicaid Services (CMS) uses to reimburse providers (Relative Value Units). Since the GAF is associated with the location of the service provider, we assign services to counties using providers' zip codes. We provide further details in Appendix C.1.

3 The Impact of Price Changes on Aggregate Care

3.1 Overall Supply Response

Our initial estimates of the effect of changes in reimbursement rates on aggregate quantities of care are shown in Figure 3. Panel A displays the year-by-year β_t coefficients from estimating equation (4). The graph shows that Medicare services respond significantly to prices, building towards an elasticity around 2.5 over the years following the price shock. Estimates for years prior to 1996 show that there was no pre-existing trend in service supply, giving us confidence in our methods of controlling for relevant county characteristics.

The year-by-year coefficients suggest that supply responses unfold over several years. These results motivate our imposition of a short- (1997 and 1998), medium- (1999 and 2000), and long-run (2001 through 2005) structure on the response for subsequent analysis. These year groupings allow us to improve precision and summarize our results in fewer coefficients.

Columns 1 through 4 of Table 2 reflect the results illustrated in Figure 3. Our baseline estimate of the health care supply elasticity (in column 1) is 0.9 in the short run, 2.1 in the medium run, and 2.7 in the long run. In column 2 we use all counties with available data, rather than just our matched sample,

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and find slightly higher estimates. Column 3 shows that the results are robust to controlling for a linear time trend in the treatment variable.[19]

Medicare periodically updates its geographic adjustments as it obtains new information on local input costs. These updates could bias our reduced-form estimates if they are correlated with the consolidation-induced price shocks and we fail to control for them. To confirm that the updates are not biasing our results, we explicitly use our price shocks as instruments within a Generalized Method of Moments (GMM) framework, as described in Appendix C.1. Column 4 shows this estimation. The results are very similar to the reduced-form estimates, suggesting that there is little correlation between price changes that occurred independent of the consolidation and health care supply shocks.

The results Table 2 are our central estimates of price responsiveness in Medicare supply. We find robust evidence for a traditional, positively sloped supply curve. The long-run elasticity of 2.7 suggests that the aggregate market is very responsive to payment rates, and we discuss the size of this response further in section 6.2.

3.2 Which Services Respond?

The welfare implications of health care supply's response to reimbursement rates depend on its health impacts, which depend in turn on which treatments are most affected. We investigate which types of services respond to reimbursements by dividing them according to a standard classification system known as Betos categories. Table 3 presents separate price elasticities for procedures,

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[19]Appendix E.1 reports a variety of additional robustness checks.

office visits, diagnostic tests, and imaging. We find large elasticities, between 1.6 and 2.9 for each broad service category.[20]

According to our model in section 1, physician concern for patient benefits means that supply responses should differ based on how valuable the care is. We test this prediction by using the medical literature to split the procedures category into more and less discretionary services. The former category includes a variety of non-essential procedures for which the timing of the treatment is highly discretionary (*e.g.*, major joint replacement, cataract removal, and a variety of musculoskeletal procedures), intensive diagnostic services (*e.g.*, catheterization and endoscopy) and procedures related to cardiac care, the intensity of which varies widely around the country. Less discretionary procedures include cancer and dialysis treatments and explicit repair procedures, such as hip fracture repair.[21]

Columns 2 and 3 of Table 3 show that the long run response of the more elective procedures is over twice that of less discretionary procedures. This result is consistent with an important role for physician agency, and by extension patient benefits, as a determinant of service supply. Physician concern for patient benefits will result in relatively small elasticities when marginal benefits drop off sharply for marginal patients. This is precisely how one might describe benefits from the category of less discretionary services. Once all hip fractures are repaired, for example, the marginal health benefit of an addi-

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[20]The Berenson–Eggers Type of Service (Betos) categories provide a mapping between each specific medical service and 106 aggregate categories of services. They are updated by CMS annually to incorporate new service codes, and are available online at `http://www.cms.gov/HCPCSReleaseCodeSets/20_Betos.asp` (accessed October 16, 2011).

[21]A detailed classification of the Betos codes is available in Appendix C.3.

tional hip fracture repair is zero.[22] These differential responses imply that the overall composition of services shifts towards more elective procedures as reimbursement rates increase.

The composition of health care may also change along other dimensions, such as service intensity and the nature of inputs. We study these adjustment margins in columns 5 and 6 of Table 2. These regressions decompose the baseline result into RVUs per service and services per beneficiary. RVUs per service approximates the intensity of the average service patients receive. The results suggest that the total response comes through both margins roughly equally; intensive services thus exhibit larger elasticities than minor services.

Appendix E analyzes care responses along several additional margins. We find strong responses in the number of providers seen by each patient, and we find that generalists and specialists respond nearly equally to reimbursement rates. We investigate the possibility that reimbursement rate changes have non-linear effects and we find no supporting evidence. Physician responses are stronger in metropolitan counties than in relatively rural areas.

3.3   Health Impacts

In column 7 of Table 2 we estimate the impact of reimbursement rates on mortality and find no significant effect. Short- and long-run point estimates suggest increased mortality in areas with price increases, and the medium-run coefficient indicates the opposite. Even at the lower bound of the 95

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[22]We present results in Appendix E showing that, for patients diagnosed with hip fractures, the likelihood of receiving a hip fracture repair is unaffected by reimbursement shocks while the number of evaluative office visits (a relatively elective service) responds.

percent confidence interval, incremental care would not be cost-effective at conventional values of a life-year (based on Cutler et al., 2006).

We also measure the effect of incremental care on self-reported health and on use of preventative care. Appendix Table E.7 reports the effect of price changes on self-reported health status using survey data from the Behavioral Risk Factor Surveillance System. The point estimates are negative and insignificantly different from zero. We can rule out health gains of 5 percent of one standard deviation or larger, and declines larger than 27 percent of one standard deviation, resulting from a 2 percent price change. Columns 2 through 6 report results for additional health outcomes and preventative care, and find no significant effects. The lack of patient benefits is probably because the quantity response is concentrated among the most elective services—the care that physicians view as least essential to their patients' health.

4 The Impact of Price Changes on Cardiac Patients

4.1 Treating Cardiovascular Disease

In this section we conduct a more detailed analysis of the care received by patients with cardiovascular disease. Heart disease is the leading cause of mortality in the United States and its treatment has made a large contribution to increased life expectancy in aggregate (Cutler et al., 2006).

We study the effect of reimbursement rates on three imaging, testing, and evaluative services that are non-invasive, low intensity and low risk. The first, echocardiography, is a technique for visualizing a patient's heart, which allows

the cardiologist to evaluate its function and anatomy. The second, a stress test, monitors a patient's blood flow and symptoms during exercise (usually, walking on a treadmill). Third, we record the number of distinct office visits experienced by each patient.

We also study the effect of reimbursement rates on the frequency of three relatively intensive procedures involving cardiac catheterization. Catheterization, which requires threading a catheter up an artery into the heart, can be both diagnostic and interventional. In addition to diagnostic catheterization, we study two related interventions: angioplasty and the insertion of stents. Angioplasty reverses arterial occlusion by expanding a balloon catheter within a blood vessel to push plaque out of the bloodstream. A stent is a metal sheath that can be installed in a coronary artery to prevent future occlusion. The medical literature contains extensive debate regarding the risks associated with angioplasty and stent insertion.

We analyze the impact of our price shocks on treatments received by cardiac patients using linear probability models of the form:

$$\text{Service}_k = \sum_{t \neq 1995} \beta_t \cdot \text{Price Change}_{i(k)} \times I_t$$
$$+ \gamma_{i(k)} + \delta_t + \eta_{s(i(k)),t} + \zeta' X_{k,i(k),t} + \varepsilon_k. \tag{5}$$

This patient-level regression uses either an indicator for whether patient k received a given service or a count of the number of services received as the outcome variable.[23] Treatment is modeled as a function of the price change

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[23]Appendix D describes our protocol for assembling cohorts of individuals with cardiovascular disease and measuring their treatments.

linked to the county $i(k)$ where patient k was diagnosed (Price Change$_{i(k)}$). We omit those diagnosed in 1996 since their one-year follow-up would include episodes of exposure to both pre-consolidation and post-consolidation reimbursement rates. We therefore use 1995 as the base year in regressions of treatment outcomes on reimbursement rate shocks (hence the $t \neq 1995$ index under the summation). Summary statistics on these patients' demographics and subsequent medical care are presented in Appendix Table E.11.

4.2   The Impact of Price Changes on Patient Care

We begin our analysis of patients with cardiovascular disease by examining the effect of reimbursement rates on the care they receive. Panel B of Figure 3 shows the impact of the 1997 price changes on the log RVUs received within one year of diagnosis. Care responds quickly after the payment area consolidation, with the estimates for all post-1996 years implying an elasticity on the order of 1. Column 1 of Table 4 reports the elasticity of 1.21 that results when the effect is pooled across all of these years. Column 2 expresses the result in levels of care rather than logs. Columns 3 through 5 report the effect of reimbursement rates on the probability that a patient receives relatively intensive procedures, specifically catheterization (whether purely diagnostic or interventional), catheterization coupled with angioplasty, and catheterization coupled with stent insertion. Column 6 reports the effect on the number of patients' evaluation and management visits, column 7 on the probability of receiving an echocardiogram, and column 8 on the probability of receiving a stress test. Services of all types exhibit significant responses to reimbursement rates. Consistent with the results in section 3, the implied elasticities are

particularly large (in excess of 2) for the procedures. Office visits exhibit the smallest elasticity, around 0.8, while the elasticities are intermediate for imaging and testing, on the order of 1.

In Panel B we divide the sample into areas in the top and bottom half of the distribution of states when ranked by the frequency with which intensive interventions are used. We proxy for this frequency using the probability that cardiac patients receive catheterizations. The elasticity of care provision is twice as large in the states that use catheterizations most frequently, with the difference being statistically distinguishable from zero at the 10 percent confidence level. Among the specific treatments, the strongest differential responses appear for diagnostic catheterizations and echocardiograms.

Panel A of Table 5 summarizes our results for total care elasticities across patient groups, adding a division of the cohorts into relatively young and old beneficiaries. Much like the differences in responses across states, where resource intensive states exhibit larger elasticities, we find that care responds most elastically for resource-intensive patients. The estimated elasticity of care for relatively old beneficiaries is nearly 40 percent larger than that for relatively young beneficiaries, although the difference is not statistically distinguishable from zero at conventional confidence levels.

4.3   The Impact of Price Changes on Patient Outcomes

Column 2 of Table 5 reports effects on the probability that beneficiaries die within 4 years of their initial diagnosis. The mortality result for the full cardiac cohort suggests that a 1 percent increase in reimbursement rates re-

duces the probability that a patient dies within 4 years by 0.04 percent. The standard error of 0.04 is sufficiently large that this value cannot be statistically distinguished from either zero or from substantially larger values.

Comparisons of mortality impacts across sub-groups of the cardiac cohorts yield richer results. Mortality reductions accrue entirely to relatively healthy and less intensively treated (at baseline) populations. Older beneficiaries appear, if anything, to experience increased mortality as a result of receiving more intensive care. While this positive point estimate is not statistically distinguishable from 0, it is statistically distinguishable from the mortality gains for younger beneficiaries at the 5 percent level. The mortality results are consistent with the view that care for these intensively-treated populations has approached "the flat of the curve." Coupled with the large elasticities associated with care for these groups, our results imply that incremental care is inefficiently allocated across the patient population.[24]

Column 3 reports results for the probability that cohort members are admitted to the hospital for treatment associated with an MI in the year following diagnosis. This constitutes an outcome of immediate concern for this particular cohort, as heart attacks are one of the principal outcomes that cardiac care is intended to prevent. The results provide no evidence that incremental care reduces the likelihood that a patient receives hospital care associated with an MI. For the full cohort, we can rule out (with 95 percent confidence) the

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[24]We estimate the effect of reimbursement rates on life expectancy more directly using Cox proportional hazard models, which are not reported. The results of this analysis exhibit a pattern similar to those shown here; modest overall mortality gains appear to be concentrated among the relatively young and among those in states associated with less intensive care regimes. Results from these models can never be distinguished statistically from zero.

possibility that a heart attack is avoided for any less than $1,000,000 in incremental expenditures. Patients appear, if anything, to become more likely to be hospitalized as the intensity of their outpatient care regime increases.[25] The evidence rejects the hypothesis that incremental outpatient care generates significant offsetting reductions in spending on inpatient care. The offsets found by Chandra, Gruber, and McKnight (2010), who focus on office visits and prescription drugs, do not materialize for the broader packages of outpatient care that we analyze.

5 The Impact of Prices on MRI Technology Diffusion

The results in sections 3 and 4 raise two questions: why are health care supply elasticities relatively large, and what drives the dynamic nature of the response? In this and the following section we consider margins likely to contribute to these features of the response. We first study investments associated with the diffusion of advanced imaging technology. In section 6 we consider adjustments in the mix of patients physicians choose to treat.

5.1 Physician Ownership of MRI Equipment

In recent years, physicians have increasingly acquired financial interests in the provision of auxiliary services, many of which require substantial capital investments and subsequently have large margins. Investments that influence profit margins can have important implications for supply elasticities. A key

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[25]This result may reflect complementarities between incremental outpatient care and hospital care rather than a worsening of health outcomes.

feature of such responses—which may include reorganization of the incentives within small-group practices, investment in new skills, and investment in referral networks—is that, as analyzed in section 1, they amplify the direct incentive effects of changes in reimbursement rates.[26]

When a patient complains of back pain, a traditional physician's office might take a detailed patient history, prescribe a painkiller, and schedule follow-up appointments. Suppose that variable costs, such as the staff time allocated to this patient, average 50 percent of a practice's typical service. For this practice, a 2 percent increase in reimbursement rates would imply a 4 percent increase in the profit margin. Suppose the practice were to install a magnetic resonance (MR) scanner and schedule back pain patients for an immediate MRI appointment, with negligible marginal costs, rather than the traditional labor-intensive treatment course. Then the profitability of incremental services will rise further. If the adjustment reduces variable costs by just 10 percent, for example, the reimbursement change's dynamic effect on the profit margin will be more than twice its static effect.

Non-radiologists have increasingly installed MR and computed tomography (CT) scanners in their offices (Levin et al., 2008). This has been increasingly common since the Stark law banned physician referrals to outside entities with which the doctor has a financial relationship (Medicare Payment Advisory Commission, 2009, p. 86). This installation can involve a variety of financial arrangements that have the common and crucial feature of giving the physician a financial incentive to use the scanner more frequently (Mitchell, 2007). Baker

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[26]In the conceptually distinct pharmaceutical setting, Yurukoglu (2012) finds evidence that payment rates affect investments in manufacturing capacity.

(2010) finds that physicians increase the use of MRIs following the acquisition of a machine.

5.2   How Do Prices Influence Physician MRI Provision?

To empirically study physician acquisition of MR scanners, we follow the procedures used by Baker (2010) to identify MRI services and determine whether they were provided by a non-radiologist physician. We first identify all claims within the Betos categories representing MRIs. We next consider the specialty of the provider listed on the claim. When the claim represents the actual performance of an MRI and is provided by an orthopedist or neurologist, we identify it as a non-radiologist MRI.[27] We then compute the fraction of unique MRI-providing firms associated with non-radiologists and the share of MRI services they represent.

Panel A of Table 6 presents evidence about the effect of reimbursement rates on the decision to invest in MR scanners. The regressions follow those in equation (4), with the prevalence of non-radiologist scanner ownership as the dependent variables. Columns 1 and 2 show the impact of the shock to reimbursement rates on the fraction of MRI-performing firms that are non-radiologist physician practices. We find coefficients around 0.4, although with marginal statistical significance. These results suggest that a one percentage point increase in reimbursement rates drives physicians' share of MRI equipment up by 0.4 percentage point. In columns 3 and 4, we investigate whether this change in the composition of MRI-providing firms translates into a change

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[27]Additional details on this procedure are provided in Appendix C.4.

in market shares. We find that it does, though for non-head/neck MRIs only. A one percentage point increase in reimbursement rates leads to a 0.35 percentage point increase in the share of non-head/neck MRI RVUs supplied by non-radiologist physicians. The lack of change in head/neck MRIs is consistent with our findings regarding elective and less-discretionary services, since MRIs of the back, in particular, tend to be relatively elective.

5.3 Back Pain Patients

To describe how changes in the provision of non-head/neck MRIs relate to changes in a broader package of care, we focus on 515,500 individuals with lower back pain. Back pain is common and often presents with no apparent cause. Deyo and Weinstein (2001) document wide cross-sectional variations in patterns of treatment, and the national time series shows a secular increase in back pain treatment intensity (Friedly et al., 2007). By definition, back pain is diagnosed on the basis of symptoms, but physicians use advanced imaging techniques to pinpoint the source of the pain. While these techniques suffer a high rate of false positives (Jensen et al., 1994), they are nonetheless employed frequently. In our sample, 9 percent of back pain patients receive a lumbar spine MRI within the year after diagnosis.

We study three treatments using the linear probability model of equation (5). The least intensive treatment is physical therapy, which twenty percent of our sample receives despite minimal evidence of effectiveness (Cherkin et al., 1998). We also study spinal injection of corticosteroids, which may generate moderate short-term benefits (Weiner et al., 2006), but which have not

been shown to reduce pain over the long term. Back pain patients can also receive spinal surgery (*e.g.*, arthrodesis, diskectomy, laminectomy, or laminotomy) in an effort to resolve problems with vertebrae or intervertebral disks. These surgeries are major operations with serious risks and limited benefits. They are performed on only two percent of our cohort members.

5.4   Back Pain Treatments

Panel B of Table 6 presents our estimates of the effect of reimbursement rates on courses of treatment for back pain. Confirming the results from section 5.2, column 1 shows that MRI provision rises with reimbursement rates, with an implied elasticity around 1. Columns 2 investigates the extent to which the incremental MRIs found in Table 6 are provided by non-radiologists. This regression looks exclusively at patients receiving MRIs, and asks whether the image was taken by a physician-owned facility. We find a strong impact of prices on that probability, with a coefficient of 0.7. A 3 percent price shock increases the probability that patients who receive MRIs have them taken by strongly-incentivized providers by 2 percentage points.

Results for back pain treatments show that—in this setting where the literature finds minimal benefits from all treatment courses—the least risky and least invasive service, physical therapy, responds most to price changes. The implied elasticity is around 2.5, which comes relative to an already high baseline rate of provision. Changes in injections and surgeries are statistically indistinguishable from zero. Moderately stronger financial incentives do not sway the typical physician to expose patients to treatments with real risks and

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minimal expected benefits. But these incentives do influence investments and provision of lucrative services with less potential for harm.

6   Substitution and Total Labor Supply

6.1   Substitution Across Patient Types

McGuire and Pauly (1991) emphasize that one potentially important response to reimbursement rates involves physicians' decisions over whom to treat. Providers can substitute between treating more profitable and less profitable patients due to either income or price effects, and changes in the incentives associated with one set of patients can influence the treatment of others (Glied and Graff Zivin, 2002). We explore the possibility that Medicare payments affect other patients' treatments using data on privately insured patients from the ThompsonReuters MarketScan ("MedStat") database.

We extract all 45 to 64-year-old privately insured patients from this database, in order to have a sample as comparable as possible to the Medicare population while not being itself eligible for Medicare. We run a regression like equation (4), using the log care supplied to privately-insured patients as the outcome. We examine how this care responds to our Medicare-specific price changes.

Results from this regression are shown in column 8 of Table 2. The point estimates are economically quite close to zero. Even so, our confidence intervals encompass a wide range of possible effects. We cannot rule out the possibility that increases in Medicare reimbursements lead to substantial substitution away from the treatment of private patients. Similarly, we cannot rule out

the increases in such treatment that would result if physicians apply uniform practice styles to all of their patients.

6.2 Physician Labor Supply Elasticities

Our baseline supply estimates yield an elasticity of Medicare services with respect to Medicare reimbursement rates of 2.5. This differs from a more traditional labor supply elasticity because the reimbursement rate is not equivalent to the physician's wage; variable costs associated with providing incremental services imply that net wages are smaller than reimbursement rates. Medicare's accounting of resource intensity implies that a physician's "own work" accounts for 40 percent of the cost of providing a typical service.[28] Consequently, we estimate that variable costs are 60 percent of baseline reimbursement rates. It follows that a 1 percent change in reimbursement rates translates into a 2.5 percent change in the physician's net wage. Hence the price elasticity of 2.5 that we have estimated represents a wage elasticity of 1.[29]

This large elasticity likely reflects both the flexibility of physicians' labor supply and their adoption of fixed cost, high margin production styles. When many firms are on the margin of making a significant investment, their responses to news about future productivity are likely to be particularly dramatic (Caballero and Engel, 1999). More firms are likely to be at this margin

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[28]This 40 percent margin is consistent with data from the American Medical Association (Wassenaar and Thran, 2003, Tables 32, 35).

[29]This elasticity is large relative to standard population-wide estimates. But it is quite comparable to estimates specific to the self-employed or to other individuals with flexible labor supply. Most directly relevant to our setting, Showalter and Thurston (1997) estimate a labor supply elasticity of 0.6 for self-employed physicians in sole proprietorships. Saez (2010) estimates elasticities around 1 for self-employed individuals with relatively low incomes.

following a period of high uncertainty (Bloom et al., 2007), and the time we study was such a period. The rapid growth of medical spending, expansion of managed care, and possibility of significant reform to the entire industry in the early 1990s set the stage for substantial responses to news about future prices from 1997 onwards. While this setting helps to explain the nature and size of the responses we find, it means that generalization to other contexts is risky. With this caveat in mind, we now ask if these results can help to explain broader trends in the health care sector.

7 Implications for U.S. Health Care Spending

Over the last half century, the U.S. health sector has grown from 5 to 18 percent of GDP. The health expenditures we study in this paper, physician and clinical services, grew from 1 percent of GDP to nearly 4 percent. Our estimates suggest that the evolution of prices can have a dramatic impact on medical spending. We illustrate this importance using recent political decisions about Medicare's overall payment rate.

To determine Medicare's reimbursement rates, the geographic adjustments we have used throughout this paper are multiplied by a national Conversion Factor (CF) as shown in equation (3). The CF evolves according to a statutory formula known as the Sustainable Growth Rate (SGR), which is intended to limit the increase of Medicare spending relative to economic growth. Beginning in 2002, the SGR formula called for a drop in payments due to higher than budgeted spending in previous years, and in that year the Conversion Factor fell by 4.8 percent (see Figure 4). But Congress subsequently prevented further

reductions in physician payments by enacting a series of temporary overrides to maintain a nearly constant Conversion Factor.

We use our estimated supply response to predict how adopting the CF required by the SGR would have influenced Medicare spending on physician services. While realized spending (the solid orange line) continues its dramatic secular increase after 2002, our estimates imply that following the SGR would have reversed this trend. As illustrated in the dashed green line, for instance, the 23 percent payment cut implied by the SGR in 2010 would have brought spending back to its level in 1992. This dramatic consequence of Congress's payment rate override shows the powerful role of provider incentives in driving medical spending.

While scaling back provider payments would be a potent tool for reducing health care spending, the CF is a blunt instrument. It affects incentives for providing both valuable and inefficient care, and a significant reduction could drive physicians out of the Medicare system.[30] One reimbursement system that could produce high-powered incentives for providing best-practice care while reducing or eliminating incentives for providing cost-ineffective care is known as payment "bundling."

As implemented in the Patient Protection and Affordable Care Act, bundling replaces fee-for-service payments with a fixed reimbursement for each episode of care. Under the logic of this system, provider groups known as Accountable Care Organizations should find it profitable to screen out physicians with reputations for providing high volumes of cost-ineffective care. Bargaining and

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[30]Mitchell and Cromwell (1982) and Paringer (1980) find that higher fees induce physicians to accept Medicare payment.

payment setting within such organizations may further generate arrangements that reward cost-efficient care and discourage unnecessary services. This bargaining may be particularly effective at reducing profit margins for technology-intensive specialties, which currently benefit from average cost reimbursement.

Under existing volume-based compensation arrangements, escalating health expenditures have created risks for public budgets (Baicker and Skinner, 2011). But these expenditures may not lead to efficient health care production (Garber and Skinner, 2008). The strength of incentive responses we find suggests that reforms to financing arrangements are a promising approach to maintain or improve care quality while reducing cost.

8   Conclusion

This paper finds that financial incentives significantly influence physicians' supply of health care. We estimate that a two percent increase in reimbursement rates across the board leads to a five percent increase in care. Physicians disproportionately adjust their provision of relatively intensive and elective treatments as reimbursements rise, and they invest in new technologies in order to do so. Our results suggest that changes in physician profit margins can explain up to one third of the growth in physician and clinical spending over recent decades.

When volume expansions generate minimal health gains, as in our setting, they can be viewed as reflecting supply-side moral hazard. Supply-side moral hazard is more potent when patients are well insured, so that physicians can increase supply without encountering significant demand-side constraints. As

analyzed by Finkelstein (2007) in the context of Medicare's introduction, insurance expansions ensure generous physician reimbursements while significantly reducing consumer exposure to out-of-pocket costs. From 1970 to 2000, the share of spending on physician services that was paid out-of-pocket declined from 45 percent to 11 percent. Resulting increases in demand-side moral hazard, coupled with increased willingness to pay for longevity (Murphy and Topel, 2006; Hall and Jones, 2007), have also played important roles in driving spending growth over this time period. Our analysis demonstrates the dramatic role that providers' incentives play within this setting. When consumers' demand for care is high and exposure to medical costs is low, physician reimbursement rates exert a major influence on treatment patterns for individual patients and health expenditures in the aggregate.

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Physician supply with price change
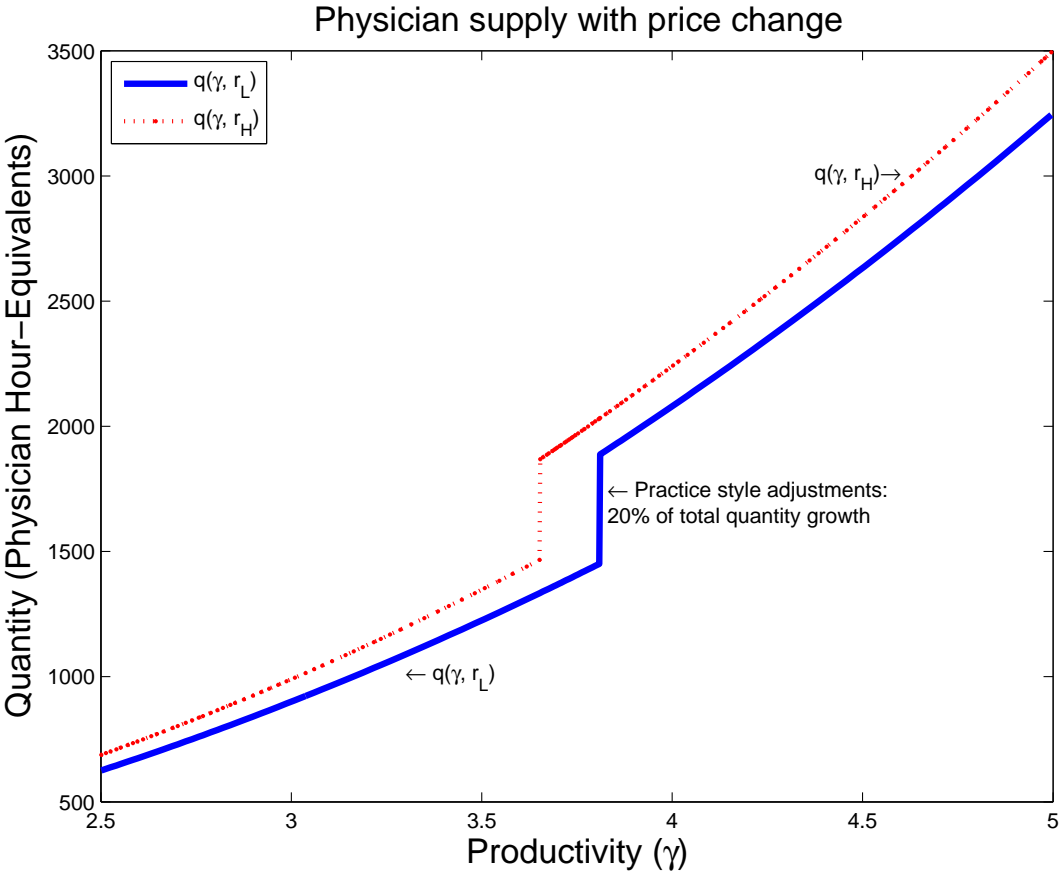
This figure illustrates the effect of reimbursement rates change on physicians' threshold γ^* for investing in an intensive practice style. At a given reimbursement rate, whether r_L or r_H, more productive physicians ($\gamma > \gamma^*$) invest in the intensive practice style, and quantity supplied is increasing with productivity γ. As shown in Proposition 1, an increase in reimbursement rates from r_L to r_H increases the quantity supplied for a physician with any fixed productivity γ, and also reduces the investment threshold γ^*, meaning that more physicians invest. The increase in supply due to the threshold shift is labeled "Practice Style Adjustments." The parameters underlying this calibration are given in Appendix A.2

Figure 2: Medicare Payment Areas
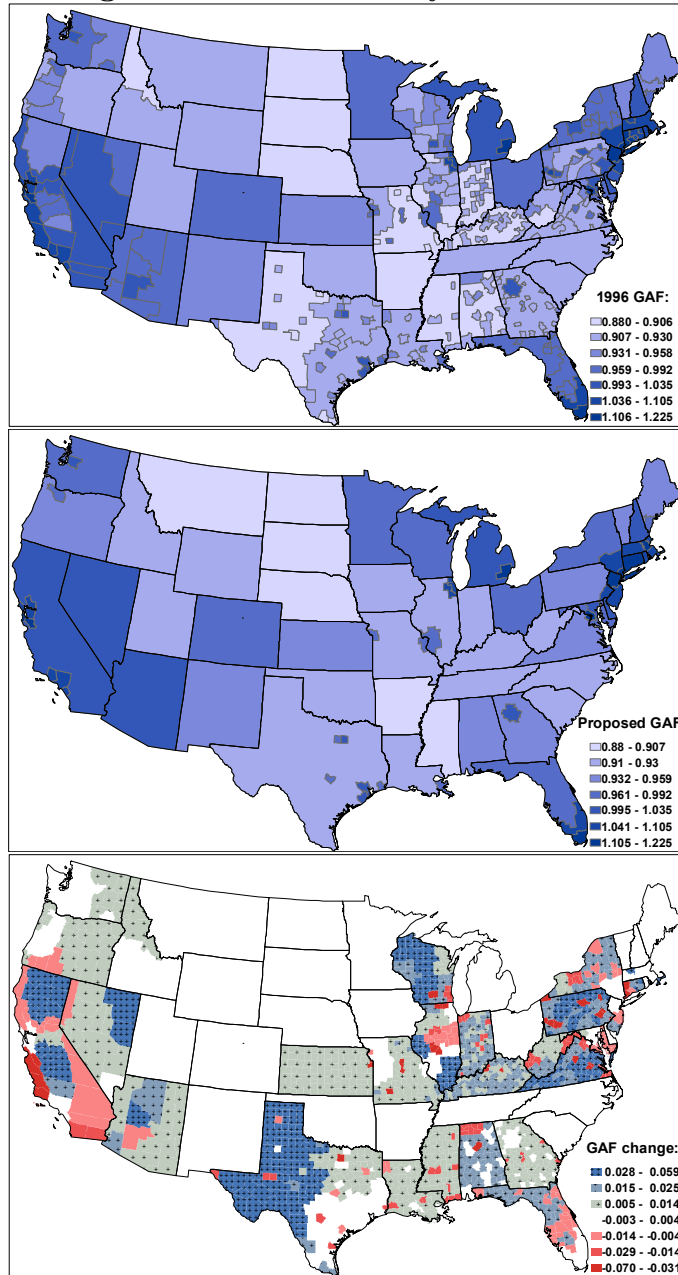
The first panel shows the 199 Medicare fee schedule areas in the continental United States as of 1996, and the second shows the 86 such localities after the consolidation in 1997. (Alaska and Hawaii were each one locality throughout this period.) The colors indicate the Geographic Adjustment Factors (GAF) associated with each Payment Locality, with darker colors indicating higher reimbursement rates. The third panel shows the change in GAF for each county due to the payment region consolidation that took place in 1997. Source: *Federal Register*, various issues.

Figure 3: **Impact of Price Change on Aggregate Quantity Supplied**

Panel A: Matched Counties

Panel B: Cardiac Patients
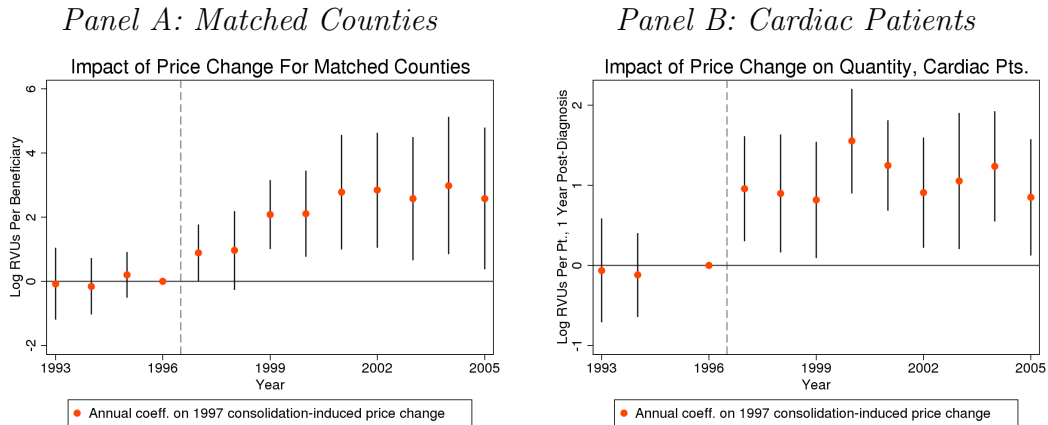
These graphs show coefficients and associated standard errors from ordinary least squares regressions in which log health care quantity supplied per Medicare patient is the dependent variable. This quantity, measured for each of 2,180 successfully matched counties (Panel A), or per Medicare patient in the cardiovascular disease cohort defined in Appendix D.1 in the year following diagnosis (Panel B), and in each year 1993–2005, is regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicator variables for each year. Coefficients correspond to β_t parameters in equation (4). Both specifications control for county fixed effects, state-by-year effects, a set of year dummy variables interacted with the log of each county's 1990 population, the fraction of beneficiaries aged 65–59, 70–74, 75–79, and 80–84, black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Figure 4: **Physician and Clinical Spending Under SGR Formula**
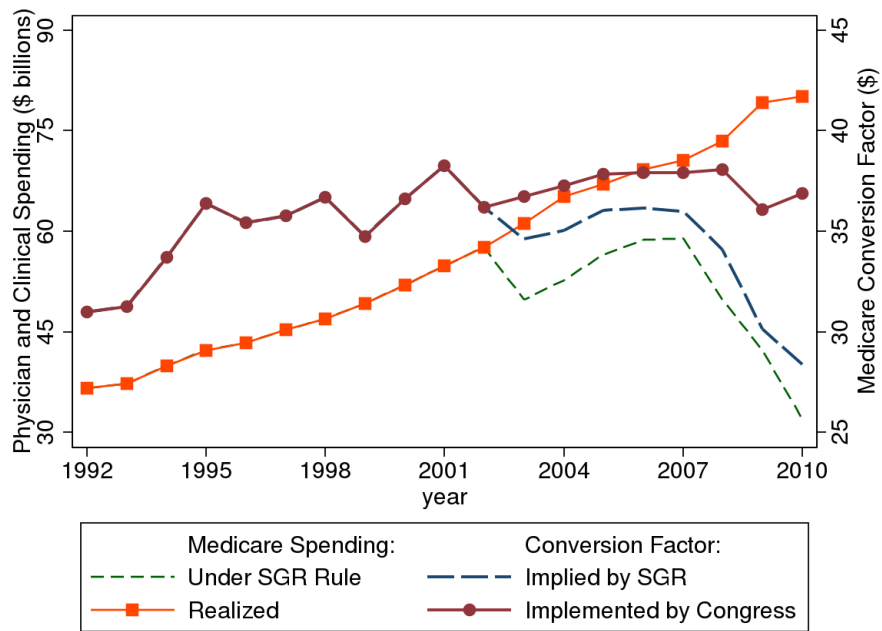
Medicare spending on physician and clinical servicse comes from the National Health Accounts (Centers for Medicare and Medicaid Services, 2011). The implemented and formula-determined Conversion Factor growth rates are from Hahn (2010) and Clemens (2011)

Table 1: **Summary Statistics**

Variable	N	Mean	Std. Dev.	Range
Consolidation-induced shock to Medicare Part B reimbursement rates				
Counties with price gain	333	-0.012	(0.012)	(-0.070, 0)
Counties with no change	1,224	0.000	(0.000)	(0, 0)
Counties with price decline	1,359	0.016	(0.011)	(0.0001, 0.059)
County population (thousands)				
Counties with price gain	333	176	(287)	(2, 2,498)
Counties with no change	1,224	109	(380)	(1, 8,863)
Counties with price decline	1,359	40	(71)	(1, 969)
Health care provided to Medicare beneficiaries, county-by-year				
RVUs per patient	37,908	18.75	17.15	(1.78, 89.14)*
Charges per patient	37,908	$ 529.80	$346.77	($87.45, $1,686.49)*

*Ranges shown from the 1st to the 99th percentile of the distribution because confidentiality requirements prevent the release of data points generated from 10 or fewer beneficiaries. Sources: Price change: *Federal Register*, various issues; county population: Census Bureau; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2.

Table 2: **Effect of Reimbursement Rate on Log Health Care Per Patient**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Aggregate Health Care Supply				Decomposition		Other Outcomes	
	Baseline	Full Sample	Trend Control	GMM	RVUs per Service	Services per Patient	Mortality	Private Quantity
Price change × Short run	0.933+ (0.489)	1.186* (0.490)	0.922+ (0.505)	0.941* (0.414)	0.572 (0.413)	0.413 (0.577)	0.00588 (0.0141)	0.263 (0.619)
Price change × Medium run	2.103** (0.586)	2.227** (0.592)	2.086** (0.647)	2.145** (0.650)	0.961* (0.440)	1.177* (0.590)	-0.0120 (0.00941)	-0.229 (0.795)
Price change × Long run	2.759** (0.925)	3.088** (0.942)	2.730** (0.908)	3.195** (1.037)	1.293* (0.609)	1.469+ (0.752)	0.00309 (0.0109)	0.044 (0.850)
Observations	28,340	37,908	28,340	28,340	28,340	28,340	28,340	25,267
Adjusted R^2	0.882	0.912	0.882		0.715	0.846	0.235	0.894
Estimation	OLS	OLS	OLS	GMM	OLS	OLS	OLS	OLS
Trend in Shock	No	No	Yes	No	No	No	No	No

$**p < 0.01$, $*p < 0.05$, $+p < 0.1$. This table reports coefficients from ordinary least squares regressions, except for column 3 which uses GMM. In columns 1 through 4, log health care quantity supplied per Medicare patient is the dependent variable. This quantity, measured for each of 2,916 counties and in each year 1993–2005, is regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. Columns 5 and 6 decompose total care into average service intensity and average number of services, respectively. The dependent variable in column 7 is the mortality rate for Medicare beneficiaries living in the county, and in column 8 is average self-reported health status from respondents aged 65 and above in the Behavioral Risk Factor Surveillance System (BRFSS). Health status is reported on a 1 to 5 scale, where 1 indicates poor health and 5 indicates excellent health. Among 376,591 respondents, the mean status is 3.12 and the standard deviation is 0.25. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. The demographic and health-based control variables are the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Table 3: **Effect of Reimbursement Rate on Log Health Care by Service Category**

Service Category:	(1) All Procedures	(2) More Elective Procedures	(3) Less Elective Procedures	(4) Evaluation & Management	(5) Tests	(6) Imaging
Price change × Short-run Post-consolidation	0.874+ (0.496)	1.600* (0.674)	-0.0916 (0.675)	1.093* (0.529)	1.335+ (0.731)	0.537 (0.610)
Price change × Medium-run Post-consolidation	2.231** (0.587)	2.923** (0.813)	1.554* (0.777)	2.147** (0.648)	1.398 (1.099)	1.390 (0.910)
Price change × Long-run Post-consolidation	2.776** (0.948)	3.689** (1.282)	1.437+ (0.755)	2.925** (1.010)	1.653 (1.692)	2.054+ (1.242)
Observations	13,767	13,767	13,767	13,767	13,767	13,767
Adjusted R^2	0.876	0.831	0.816	0.903	0.866	0.874

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient in each category is the dependent variable. These quantities, measured for each of 1,527 counties and in each year 1993–2005, are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, a set of year dummy variables interacted with the log of each county's 1990 population, the fraction of beneficiaries aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; Betos definitions: Centers for Medicare and Medicaid Services; county population: Census Bureau.

Table 4: **Effect of Reimbursement Rate on Treatment of Cardiovascular Disease**

	(1) Log Care	(2) Total Care	(3) Cath	(4) Stent	(5) Angioplasty	(6) Physician Visits	(7) Echo	(8) Stress Test
Panel A: All Patients With Cardiovascular Disease								
Price change	1.210**	67.33**	0.122**	0.0222+	0.0225+	7.540*	0.147*	0.130**
× Post-Consolidation	(0.250)	(21.38)	(0.0283)	(0.0121)	(0.0130)	(2.182)	(0.0648)	(0.0432)
Sample Mean	3.209	54.33	0.0534	0.00797	0.00856	9.192	0.153	0.112
Elasticity			2.33	2.84	2.63	0.82	0.94	1.16
Panel B: Treatment Effect Heterogeneity by Baseline Cath. Intensity								
Price change	0.830*	19.59	0.114**	0.00446	0.0283*	6.027+	0.0949	0.0868+
× Post-Consolidation	(0.325)	(49.08)	(0.0612)	(0.0253)	(0.0304)	(3.087)	(0.151)	(0.109)
Price change	0.981+	152.4**	0.109+	0.0159	0.0187	4.922	0.316*	0.0234
× Post-Consolidation	(0.543)	(49.08)	(0.0612)	(0.0253)	(0.0304)	(4.363)	(0.151)	(0.109)
× High Cath. Intensity								
Observations	689,684	696,550	696,550	696,550	696,550	696,550	696,550	696,550

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which the treatment received by patients with cardiovascular disease is the dependent variable. The sample is restricted to patients living in counties that satisfy our matching requirements, as described in the text (the results are essentially unchanged when we include the complete cohort defined in Appendix D.1). In Panel B, states are classified based on whether the entire state has an above-median share of patients with cardiovascular disease who receive this treatment. The dependent variable in columns 1 and 2 is total quantity of care, expressed in logs and levels, and in columns 3 through 8 is an indicator for receiving the relevant treatment in the year after diagnosis (excepting physician visits, reported in column 6, which are expressed as counts). These quantities, measured for each patient, are regressed on the reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, in the county where the patient was first diagnosed, interacted with an indicator for years after the consolidation. All specifications control for fixed effects by county of diagnosis, state-by-year effects, and indicators for the patient's age, being black, Hispanic, female, being eligible for Medicare due to end-stage renal disease, and being eligible for Medicare due to disability. The results are robust to controlling additionally for each patient's health as proxied for by a set of indicators for having the individual comorbidities defined by Elixhauser et al. (1998), as well as having 2, 3, 4, and 6 or more such comorbidities. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Table 5: Effect of Reimbursement Rate on Cardiac Patients

Outcome:	(1) Log Care	(2) Mortality within 4 Years	(3) MI Hosp. within 1 Year
Panel A: Full Sample			
Price change ×	1.133**	-0.0390	0.0264+
Post-Consolidation	(0.241)	(0.0408)	(0.0147)
Panel B: Treatment Effect Heterogeneity by Patient Age			
Price change ×	0.996**	-0.107*	0.0279
Post-Consolidation	(0.231)	(0.0462)	(0.0178)
Price change ×	0.612	0.214*	0.0120
Post-Consolidation ×	(0.421)	(0.104)	(0.0373)
Age ≥ 75			
Panel C: Treatment Effect Heterogeneity by State-Level Cath Intensity			
Price change ×	0.830*	-0.0751	0.0277+
Post-Consolidation	(0.325)	(0.0455)	(0.0162)
Price change	0.981+	0.117	-0.00433
× Post-Consolidation	(0.543)	(0.0919)	(0.0345)
× High Cath. Intensity			
Observations	689,684	696,550	696,550

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions for the following patient care and health-related outcomes: total care (column 1), an indicator for whether the patient dies within 4 years (column 2), and an indicator for whether the patient is hospitalized for MI (heart attack) during the first year following the initial diagnosis of cardiovascular disease (column 3). The sample is restricted to patients living in counties that satisfy our matching requirements, as described in the text (the results are essentially unchanged when we include the complete cohort defined in Appendix D.1). In Panel C, states are classified based on whether the entire state has an above-median share of patients with cardiovascular disease who receive this treatment. The outcomes are regressed on the reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, in the county where the patient was first diagnosed, interacted with an indicator for years after the consolidation. All specifications control for fixed effects by county of diagnosis, state-by-year effects, and indicators for the patient's age, being black, Hispanic, female, being eligible for Medicare due to end-stage renal disease, and being eligible for Medicare due to disability. The results are robust to controlling additionally for each patient's health as proxied for by a set of indicators for having the individual comorbidities defined by Elixhauser et al. (1998), as well as having 2, 3, 4, and 6 or more such comorbidities. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Table 6: **Effect of Reimbursement Rate on MRI Ownership and Back Pain Treatment**

	(1)	(2)	(3)	(4)	(5)
Panel A: Non-Radiologist MR Scanner Ownership					
Physician-Owned Share of:	Firms Performing MRI		MRIs Performed		
MRI Category:	Head/Neck	Non-Head/Neck	Head/Neck	Non-Head/Neck	
Price change ×	0.423+	0.459+	0.171	0.351*	
Post-consolidation	(0.245)	(0.269)	(0.139)	(0.167)	
Observations:	6,766	6,868	6,868	6,766	
Panel B: Treatment of Back Pain Patients					
Service:	Any MRI	Physician-Owned MRI	Physical Therapy	Injection	Surgery
Price change ×	0.113*	0.689**	0.530**	-0.001	0.040
Post-consolidation	(0.0503)	(0.206)	(0.061)	(0.033)	(0.026)
Sample Mean	0.091	0.43	0.21	0.036	0.021
Observations	515,500	47,147	515,500	515,500	515,500

$**p < 0.01$, $*p < 0.05$, $+p < 0.1$. Panel A reports coefficients from ordinary least squares regressions in the dependent variables measure non-radiologist physician ownership and provision of magnetic resonance imaging (MRI) services provided to Medicare beneficiaries. Non-radiologist physician ownership of MRI imaging is defined in section 5.2, following the method outlined in Baker (2010). Panel B reports coefficients from regressions in which the treatment received by each Medicare patient in the back pain cohort as defined in Appendix D.1 is the dependent variable. These variables expressed as an indicator for receiving a given treatment at least once in the year after diagnosis. Column 2 is conditional on having some MRI taken during the year following diagnosis; all other columns include the entire cohort. These indicators and shares are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, in the county where the patient was first diagnosed, as interacted with an indicator for years after the consolidation. All specifications control for county fixed effects and state-by-year effects. They also control for the patient's age group (65–59, 70–74, 75–79, and 80–84), being black, Hispanic, female, eligible for Medicare due to end-stage renal disease, enrolled in an HMO, and each comorbidity defined by Elixhauser et al. (1998), as well as having 2, 3, 4, and 6 or more such comorbidities. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix For Online Publication Only

A Solution to Model of Physician Practice Style

Equations (1) give the physician's utility levels conditional on adopting the standard practice style and the intense style, respectively:

$$U_S(q; \gamma_i) = (r - \bar{c})q - e\left(\frac{q}{\gamma_i}\right) + \alpha b(Q)q$$

$$U_I(q; \gamma_i) = (r - \underline{c})q - e\left(\frac{q}{\gamma_i}\right) + \alpha b(Q)q - k \tag{6}$$

Conditional on the physician's discrete investment decision, physician labor and variable inputs are adjusted continuously to optimize the production level. Holding the practice style given, the physician therefore chooses the quantity to supply according to the following first-order conditions:

$$0 = (r - \underline{c}) - \frac{1}{\gamma_i}e'\left(\frac{q_I^*}{\gamma_i}\right) + \alpha b(Q) \tag{7}$$

$$0 = (r - \bar{c}) - \frac{1}{\gamma_i}e'\left(\frac{q_S^*}{\gamma_i}\right) + \alpha b(Q). \tag{8}$$

The equilibrium supply quantity is denoted by q_I^* if she has invested in the intense style and q_S^* if she has not. It immediately follows from equations (7) and (8) that physicians supply more care when they invest, so $q_I^* > q_S^*$.

A.1 Proof of Proposition 1

Proposition 1 states:

Proposition 1 *There exists a threshold productivity γ^* such that physicians invest if and only if $\gamma > \gamma^*$. The threshold decreases in the reimbursement rate r and in the weight placed on patient benefits α. Aggregate supply increases in the reimbursement rate, with a slope given by*

$$\frac{dQ}{dr} = \underbrace{\int_0^{\gamma^*(r)} \frac{dq_S^*(\gamma)}{dr} f(\gamma)d\gamma}_{\text{Standard practice style}} + \underbrace{\int_{\gamma^*(r)}^{\infty} \frac{dq_I^*(\gamma)}{dr} f(\gamma)d\gamma}_{\text{Intensive practice style}} - \underbrace{\frac{d\gamma^*}{dr} f(\gamma^*)\left[q_I^*(\gamma^*) - q_S^*(\gamma^*)\right]}_{\text{Physicians switching practice styles}}. \tag{9}$$

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To prove the existence of the threshold, we consider the relationship between the benefits from investing and physician effort costs. A physician prefers to invest if and only if the utility achieved while investing is superior to that achieved without investing. We show that this is true for physicians with sufficiently high productivity, not true for physicians with low productivity, and the net benefit increases monotonically in productivity between these two extremes. The intermediate value theorem then implies the result.

We denote the net utility gain from investing in the intense practice style as $\Delta(\gamma)$ for a firm with effort cost γ. This is given by

$$\Delta(\gamma) = (r - \underline{c})q_I^*(\gamma) - e\left(\frac{q_I^*(\gamma)}{\gamma}\right) + \alpha b(Q)q_I^*(\gamma) - k - \left\{(r - \bar{c})q_S^*(\gamma) - e\left(\frac{q_S^*(\gamma)}{\gamma}\right) + \alpha b(Q)q_S^*(\gamma)\right\}$$

The net benefit to investing is increasing in productivity whenever its derivative with respect to γ is positive. Invoking the Envelope Theorem, this derivative is:

$$\Delta'(\gamma) = \frac{e'(q_I^*(\gamma)/\gamma) - e'(q_S^*(\gamma)/\gamma)}{\gamma^2}. \tag{10}$$

Because $q_I^* > q_S^*$ for all values of γ, this derivative is always positive.

To complete the proof, we need to see that $\Delta(\gamma) < 0$ for a low value of γ and $\Delta(\gamma) > 0$ for a high value. Because $e(0) = 0$, there exists a sufficiently high $G \in (0, \infty)$ such that $q_I^*(G)$ is large enough to ensure that $q_I^*(G)(\underline{c} - \bar{c}) \geq k$ so the investment is worthwhile. To ensure that $\Delta(\gamma) < 0$ at some point, we look to the opposite extreme of the productivity distribution. As productivity approaches zero, so does production. So there exists $\varepsilon > 0$ such that quantity $q_I^*(\varepsilon)$ at this productivity level is sufficiently low that the incremental revenues from investing do not cover the cost of the investment, or $q_I^*(\varepsilon)(\underline{c} - \bar{c}) < k$. At this effort cost $\gamma = \varepsilon$, the net income from investing is lower than the net income when not investing, while the effort cost is still increasing with the investment, since $q_I^* > q_S^*$, so $\Delta(\varepsilon) < 0$.

This proves of the statement about the existence of the γ^* threshold. We now demonstrate the second statement, regarding the relationship between γ^* and the reimbursement rate r. To determine how the investment threshold moves with r, we first note that the threshold itself is defined by $\Delta(\gamma^*) = 0$, or

$$(r - \underline{c})q_I^*(\gamma^*) - e\left(\frac{q_I^*(\gamma^*)}{\gamma^*}\right) + \alpha b(Q)q_I^*(\gamma^*) - k = (r - \bar{c})q_S^*(\gamma^*) - e\left(\frac{q_S^*(\gamma^*)}{\gamma^*}\right) + \alpha b(Q)q_S^*(\gamma^*)$$

We differentiate this with respect to r, again using the Envelope Theorem, and letting e'_I denote the marginal effort cost for a provider of productivity who chooses to invest, and v'_S the marginal cost for one who doesn't:

$$q_I^*(\gamma^*) + \frac{q_I^*(\gamma^*)}{\gamma^{*2}}e'_I\frac{d\gamma^*}{dr} + \alpha b'(Q)\frac{dQ}{dr}q_I^*(\gamma^*) = q_S^*(\gamma^*) + \frac{q_S^*(\gamma^*)}{\gamma^{*2}}e'_S\frac{d\gamma^*}{dr} + \alpha b'(Q)\frac{dQ}{dr}q_S^*(\gamma^*).$$

Solving for the derivative $\frac{d\gamma^*}{dr}$ yields:

$$\frac{d\gamma^*}{dr} = -\left[1 + \alpha b'(Q)\frac{dQ}{dr}\right]\frac{\gamma^{*2}\left[q_I^*(\gamma^*) - q_S^*(\gamma^*)\right]}{q_I^*(\gamma^*)e'_I - q_S^*(\gamma^*)e'_S} \tag{11}$$

Since the fraction on the right-hand side of equation (11) is always positive, the sign of $d\gamma^*/dr$ depends on whether $1 + \alpha b'(Q)dQ/dr > 0$.

Holding fixed the practice style, a physician's price response is:

$$\frac{dq^*}{dr} = \left[1 + \alpha b'(Q)\frac{dQ}{dr}\right]\frac{\gamma_i^2}{e''\left(q/\gamma_i\right)}, \tag{12}$$

whose sign depends on the same expression $1 + \alpha b'(Q)dQ/dr$, since $e''(\cdot) > 0$.

Because of the threshold's existence, aggregate supply can be written as

$$Q(r) = \int_0^{\gamma^*(r)} q_S^*(\gamma)f(\gamma)d\gamma + \int_{\gamma^*(r)}^{\infty} q_I^*(\gamma)f(\gamma)d\gamma, \tag{13}$$

whose derivative is given in (9). The sign of dQ/dr depends on the signs of dq_S^*/dr, dq_I^*/dr, and $d\gamma^*/dr$. Suppose that $dQ/dr < 0$. Because $b'(Q) < 0$, the expression $1 + \alpha b'(Q)dQ/dr$ that controls the signs of these three derivatives is consequently positive, which means that $dq_S^*/dr > 0$, $dq_I^*/dr > 0$, and $d\gamma^*/dr < 0$. Hence $dQ/dr > 0$, which contradicts the supposition. Thus $dQ/dr \geq 0$, as asserted in the Proposition.

Since $dQ/dr \geq 0$, the expression $1 + \alpha b'(Q)dQ/dr$ is positive unless marginal benefits of care decline very rapidly ($b'(Q)$ is significantly negative) and doctors put a high weight (α) on these benefits. Suppose this were sufficiently true that $1 + \alpha b'(Q)dQ/dr < 0$. Once again, this would mean that $dq_S^*/dr < 0$, $dq_I^*/dr < 0$, and $d\gamma^*/dr > 0$, and hence $dQ/dr < 0$. But, as just shown, $dQ/dr \geq 0$.

This contradiction means that $1 + \alpha b'(Q)dQ/dr \geq 0$, and hence $d\gamma^*/dr < 0$, as asserted in the Proposition. Since $1 + \alpha b'(Q)dQ/dr \geq 0$, we also have $dq_S^*/dr \geq 0$ and $dq_I^*/dr \geq 0$, so $dQ/dr \geq 0$, as also asserted.

Similar logic shows that supply is increasing in α. The investment threshold moves with α according to

$$\frac{d\gamma^*}{d\alpha} = -\left[b(Q) + \alpha b'(Q)\frac{dQ}{d\alpha}\right] \frac{\gamma^{*2}\left[q_I^*(\gamma^*) - q_S^*(\gamma^*)\right]}{q_I^*(\gamma^*)e_I' - q_S^*(\gamma^*)e_S'},$$

which depends on the sign of the same term as does $dq/d\alpha$ within each investment regime:

$$\frac{dq^*}{d\alpha} = \left[b(Q) + \alpha b'(Q)\frac{dQ}{d\alpha}\right] \frac{\gamma_i^2}{e''\left(q/\gamma_i\right)}.$$

If $dQ/d\alpha$ were negative, we would have $dq^*/d\alpha > 0$ and $d\gamma^*/d\alpha < 0$, contradicting $dQ/d\alpha < 0$. If $b'(Q)$ were sufficiently negative and α sufficiently large that $b(Q) + \alpha b'(Q)dQ/d\alpha < 0$, then $dQ/d\alpha < 0$, but the previous sentence demonstrates that $dQ/d\alpha \geq 0$. Thus $b(Q) + \alpha b'(Q)dQ/d\alpha \geq 0$, so $d\gamma^*/d\alpha < 0$, as the Proposition asserts.

A.2   Quantitative Calibration

Figure 1 comes from a calibration of this model under the following assumptions:

$$
\begin{aligned}
e(z) &= \frac{z^2}{1000} \\
b(Q) &= \frac{1}{Q} \\
r_L &= \$200 \\
r_H &= \$210 \\
\underline{c} &= \$70 \\
\bar{c} &= \$100 \\
k &= \$100,000 \\
\alpha &= 0.01
\end{aligned}
$$

We assume that productivity γ is distributed according to a generalized Pareto distribution, with parameters 5, 4, and 2.5, and truncated at 5, so that γ takes on values from 2.5 to 5.

B Brief History of Medicare Physician Payments

B.1 Medicare Fee Schedule for Physician Services

Our estimate of how price shocks influence health care provision relies on a number of institutional details about provider payments in the Medicare health insurance system. We therefore include an overview of the Medicare payment system here to strengthen our assumption about the exogeneity of certain price shocks, as argued briefly in section 2.[31]

When Medicare was created by the Social Security Act of 1965, physicians were largely skeptical of federal interference in the practice of medicine, raising concern that they might not participate in the program (Newhouse, 2003). To encourage their participation, Medicare gave doctors freedom to set their own prices, subject to the constraint that the charges were comparable with the "customary, prevailing and reasonable" rates in the physician's practice area (eventually known as a Fee Schedule Area [FSA] or Medicare Payment Locality [MPL]). Tying reimbursement rates to a physician's practice area would ensure that physicians in high-cost urban areas could obtain reimbursements commensurate with their expenses, while allowing lower reimbursements to be paid to physicians in lower-cost rural areas.

The Health Care Financing Administration (HCFA; now the Center for Medicare and Medicaid Services, or CMS) oversaw Medicare's implementation by hiring contractors (or "carriers") to administer the program in each state. The contractors, who generally had responsibility for one state each, determined which geographic areas would constitute a unique health care market. This decentralized process led to dramatic differences in the distribution of regions across states, as illustrated in the top panel of Figure 2.[32] Wisconsin had eight regions, for example, while neighboring Minnesota (a state of similar population) had only one; Texas had 32 while more populous California had 21. Areas shown in darker shades on the map have higher relative reimbursement rates, while lighter-colored areas have lower prices. As the map makes clear, reimbursement rates are correlated with population or density, as urban areas tend to have higher reimbursements than lower-cost rural areas.

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[31]Newhouse (2003, ch. 1) presents a detailed history of these payments, including many facets that are omitted here.

[32]In the instances when a county was split into different Payment Localities, we assign it to the "more urban one", as specified in 61 *FR* 34631 (1996) on the assumption that most medical services in the pre-consolidation era probably took place in the urban and better-reimbursed part of the county.

The Payment Localities shown in the top panel of Figure 2 served as the basis for geographic reimbursement differentials from 1965 through the early years of the Resource Based Relative Value Scale (RBRVS) fee schedule.[33] Through the RBRVS fee schedule, HCFA established a quantity measure for each of 8,677 unique services (a number that had expanded to 13,223 by 2005)[34] and a per-unit price index specific to the Locality in which a service was provided. RBRVS was legislated through the Omnibus Budget and Reconciliation Act of 1989,[35] was implemented beginning in 1992[36], and remains in place today. The units of quantity are called Relative Value Units (RVUs) and are intended to measure the real resource intensity associated with providing a given service (Hsiao et al., 1988). The price measure is called the Geographic Adjustment Factor (GAF), which varied across space to account for differences in input costs across the Payment Localities.[37] Within each Locality, the GAF is computed on the basis of average input costs across the counties in the locality.

These input costs are organized into three categories, both for the purpose of determining resource intensity (the RVUs for a service) and for calculating area-specific input prices (the GAF). These categories are known as physician work, practice expense (PE), and malpractice expense (MP). The physician work RVUs are intended to capture "the financial value of physicians' time, skill, and effort that are associated with providing the service" (GAO, 2005, p. 5). CMS computes a Geographic Practice Cost Index (GPCI) associated with physician work in order to account for the different value of physician labor across areas. The work GPCI is computed based on wages of other professionals in the area, and the differences across payment localities are then scaled down by three-quarters (GAO, 2005, p. 7).[38]

The other two types of RVUs are intended to capture the costs of other

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[33]Some minor changes occurred, but the 1965 Payment Localities were left largely intact through 1996, which is the year of the localities shown on the map (61 *Federal Register* 59494 [1996]).

[34]The list of services and associated Relative Value Units is provided by CMS at `http://www.cms.gov/PhysicianFeeSched/01_overview.asp` (accessed October 16, 2011).

[35]Pub. L. 101-239 (1989).

[36]56 *FR* 59502 (1991)

[37]The presence of such an adjustment may not be theoretically optimal, but it seems to be politically necessary because of concerns about beneficiaries' access to care in whichever geographic region they choose.

[38]The scaling of work GPCI results from the tension between adjusting prices to accurately compensate for local input costs—hence the existence of GPCIs—and the desire to equalize urban/rural payment differentials. Congress occasionally changes the rules regarding GPCI adjustments, such as arbitrarily imposing a floor on the work GPCI from 2004 through 2006 and on all GPCIs in Alaska in 2005 and 2005 (GAO, 2007, p. 7).

inputs that a physician purchases to perform various services. The practice expense RVUs represent the office rent, staff time, and supplies and equipment needed to perform a service. It includes both fixed costs, such as office rent and capital equipment, and some variable costs such as staff time and disposable supplies. The PE GPCI attempts to adjust for the costs of these inputs across regions, and CMS computes it based on estimates of wages among occupations that supply physicians with inputs (nurses, health technicians, and administrative staff) and area rents. Finally, the malpractice expense RVUs capture a particular service's contribution to the physician's annual malpractice insurance premium. Malpractice insurance premiums are generally fixed annual costs per physician, regardless of the number of services performed. As with part of the PE RVUs, reimbursement for malpractice insurance constitutes an attempt to pay physicians their average costs rather than marginal costs. Malpractice premiums are generally relatively constant within a state, so the MP GPCI varies mostly at the state level rather than within states.

Because reimbursement for a particular service is based on three types of RVUs, each with an associated GPCI, equation (3) was a slight simplification. It is more accurate to model reimbursements for a given service j in area i at time t as:

$$\text{Reimbursement}_{i,j,t} = \text{Conversion Factor}_t \times \tag{14}$$

$$\sum_{type \in \{\text{Work, PE, MP}\}} \text{Relative Value Units}_{type,j} \times \text{Geographic Practice Cost Index}_{type,i}.$$

To escape the endogeneity of both the level of the GAF and the changes due to its regularly scheduled updates, we exploit a substantial one-time change in Medicare's system of geographic adjustments, which took place in 1997 and is described in section 2.

B.2   Contemporaneous Changes in Medicare Payments

The payment area consolidation that supports our identification of supply responses to reimbursement rates took place during an era of many changes in the health care industry. Medicare itself changed many payment policies during the 1990s, largely as a result of Congressional action, and Newhouse (2002; 2003) provides extensive histories of these changes. Cutler and Gruber (2002) discuss other changes to federal payment policies during the 1990s that could affect the Medicare market by changing patients' or providers' behavior. We discuss the most relevant of these changes here to show that they do not threaten our identification strategy.

The introduction of the Resource-Based Relative Value Scale (RBRVS) to determine Medicare Fee Schedule payments starting in 1992 led to dramatic changes in health care supply. The long-term rapid growth in Medicare spending on physician services briefly paused for three years (Newhouse, 2002, Figure 13.1), while health spending overall grew less rapidly than before or after that period (Cutler and Gruber, 2002, Figure 12.3). This change is an important part of the long-term history of Medicare spending and the RBRVS, but was a national shock that should not differentially affect supply trends within states based on their consolidation status.

Since the RBRVS was introduced, Congress has frequently tinkered with the Conversion Factor that scales RVUs into dollars (Newhouse, 2003, ch. 1). Surgeons had a separate (higher) Conversion Factor for a period, and it is eminently plausible that this could differentially affect supply in areas with different proportions of services. The Balanced Budget Act of 1997 (BBA)[39] introduced a new permanent rule for updates to the Conversion Factor. This rule, known as the Sustainable Growth Rate (SGR), replaced the prior Volume Performance Standard and was intended to link Medicare spending to GDP growth. But as soon as the Balanced Budget Reconciliation Act of 1999 (BBRA),[40] Congress began adjusting payments off of the trend set by the SGR formula. Both systematic and idiosyncratic changes to the Conversion Factor influence payment rates for the services we study, but our empirical strategy accounts for such effects and our central identifying assumption is robust to Conversion Factor changes. First, time fixed effects account for the nationwide changes imposed by the adoption of SGR and its subsequent updates. Second, control states that experienced no consolidation, but have counties with similar characteristics to states that experienced consolidations, account for time-varying effects that might result from temporarily paying surgeons more than non-surgeons. Third, the timing of our estimated supply responses coincides with the shock induced by the payment area consolidation.

BBA and BBRA also changed Medicare payment policies for hospitals, post-acute care facilities, home health care providers, and Health Management Organizations serving Medicare beneficiaries. Newhouse (2002) argues that these payment changes had significant impacts on use of services that may be complements or substitutes with physician care. The impacts of Medicare payment rates on total spending depend on these potential interactions, but our geographically-based estimates do not. As long as these payment rates have similar effects on counties with similar observable characteristics, our controls for time-varying effects of county population and our matching esti-

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[39]Pub. L. 105-33 (1997)
[40]Pub. L. 106-113 (1999)

mator will account for effects of these changes independent of the payment area consolidation shocks.

The Medicare Modernization Act of 2003 (MMA)[41] was enacted towards the end of our sample period and introduced Medicare Part D to cover outpatient prescription drugs. Part D was not implemented until 2006, after our sample ends, so changes in substitution patterns between office visits and drug purchases will not influence our estimates. The MMA also changed the GAF for certain payment areas in 2004 through 2006. Alaska was granted idiosyncratic increases in each GPCI to 1.67 in 2004 and 2005. The MMA also imposed a minimum work GPCI of 1, so payment variation was reduced in the lowest-cost rural areas. This largely affected statewide payment areas in low-cost states that had previously experienced payment locality consolidations, although some sub-state areas were also affected. Our GMM results, shown in column 3 of Table 2, account for these GAF changes and yield very similar estimates to the baseline OLS specifications.

National and state-level changes to Medicaid payments and eligibility can spill over into private and Medicare markets (Glied and Graff Zivin, 2002), and our period of analysis included numerous such changes (Clemens, 2012). But the state-based nature of the Medicaid program means that such spillovers should affect positively and negatively price-shocked areas identically. Medicaid payment rates are set by individual states, and eligibility is determined by a combination of state and federal policy. Thus our state-by-year fixed effects should effectively account for these changes.

B.3   Additional Details on Payment Area Consolidation

In general, the payment region consolidation merged together previously distinct fee schedule areas, but there are a few small exceptions to this pattern. Before the consolidation, Massachusetts had an "urban" payment region including the Boston and Worcester areas, and after the consolidation Worcester was split apart from Boston and merged with rural Massachusetts. Similarly, Pennsylvania had grouped Philadelphia and Pittsburgh together prior to the consolidation, and they were split apart afterwards, with Pittsburgh joining the "Rest of Pennsylvania" (excluding Philadelphia) region.

The Medicare fee schedule had 210 payment areas up through 1996. Los Angeles County had eight distinct fee schedule regions, all of which had the same payment rates, so we treat them as one. We drop Puerto Rico and the U.S. Virgin Islands, and we also exclude Alaska from our dataset because of changes in the definitions of some county-equivalent geographic units during

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[41]Pub. L. 108-173 (2003)

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this sample period, leaving us with 200 pre-consolidation payment areas in our data.

B.4 Previous Payment Area Consolidation

In one of the first studies of health care supply with a credible identification strategy, Rice (1983) studies the effects of reimbursement rates on the supply of physician services using a similar geographically-determined shock to the calculation of Medicare "prevailing charges" in the state of Colorado in 1976. Our empirical context is national in scope and hence has several advantages over that utilized by Rice. First, the consolidation generated shocks to prices in 145 of the 210 initial payment localities. This allows us to conduct our analysis at an aggregate geographic level and hence incorporate extensive margins, such as physician participation in Medicare, that previous work at the physician level cannot capture. Also due to the number and variability of our shocks, we obtain reasonable statistical power even while allowing conservatively for correlated errors at the level of the old payment localities.

Second, Rice's consolidation and our consolidations all increased reimbursement rates in a manner negatively correlated with urban density. We use the experience of states that were unaffected by the consolidation to control for differential trends across urban and rural areas. Such controls involving unaffected states were not available to Rice due to data limitations. We are able to study the evolution of care over an extended time period, allowing us to control directly for pre-existing trends that were correlated with the changes in the reimbursement rates. We are also able to follow the dynamics of care provision for close to ten years following the shock to prices. Third, the federal imposition of the consolidation may mitigate concerns that the policy change occurred in response to the experience of a particular health care market.

Finally, Medicare's reimbursement policy was more flexible during the 1970s, when Rice's Colorado consolidation took place. At that time, providers were not obligated to accept Medicare's determination of reimbursement rates, and physicians' willingness to accept Medicare's preferred payment rates is one of the margins that responded to prices in general (Mitchell and Cromwell, 1982) and to the 1976 Colorado price shock in particular (Rice and McCall, 1982). We have the advantage of studying an era when prices were strictly determined by the Medicare fee schedule, so providers' price behavior was constrained and all adjustments take place on the quantity margin.

C Data Appendix

C.1 Medicare Claims Data

In our baseline specification we take several measures to reduce the potential impact of outlier observations. Outliers can have profound effects in studies of health care due to the long right tail of the health spending distribution. Although we have aggregated observations at the county level, outliers remain a concern because the aggregates for many small counties are estimated using a small number of observations. To limit the effect such outliers we take three steps. First, we weight each county-by-year observation by the number of unique patients receiving care in that county in that year, thus limiting the influence of small-sample observations. This makes our results interpretable as estimates of changes in the average quantity of care across patients rather than across counties. Second, we use diagnosis information to construct a standard set of variables indicating the comorbidities affecting each Medicare beneficiary (Elixhauser et al., 1998).[42] In the county-level regressions we account for these health status indicators by controlling for the share of each county's sample population that has two, three, four, and six or more of these comorbidities. We also control for a set of sample-specific demographic variables—the share of beneficiaries in that county belonging to the age groups 65–69, 70–74, 75–80, 80–84, and 85 or more years old, the share female, the shares black and Hispanic, and and the fraction of the beneficiary population eligible for Medicare due to end-stage renal disease—and for the fraction of a county's sample of Medicare beneficiaries that receives coverage through a Medicare Advantage HMO. As a final step, we winsorize the sample at the 1st and 99th percentiles.

Summary statistics computed from these data are presented in Table 1. We split counties into the 333 with a negative price shock from the consolidation, the 1,359 with a positive shock, and the 1,224 counties not involved in a consolidation. Table 1 confirms that the average price increase is larger than the average decline, and areas experiencing negative price shocks tend to be larger, denser, and more frequently in a metropolitan area.[43] As a result, they tend to treat more patients annually, provide substantially more care, and receive substantially more Medicare charges. Aggregating the three groups together,

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[42]The number of diagnoses could certainly be endogenous with respect to the GAF, but we find no evidence for a response of diagnoses to the consolidation-induced shock physician reimbursement rates.

[43]Metropolitan area counties are defined using the Office of Management and Budget's 1999 definitions, with all counties in a Metropolitan Statistical Area or New England Consolidated Metropolitan Area considered to be metropolitan.

the claims data include nearly 51 million claims annually, representing 74 million RVUs, which together are worth \$2.7 billion. These claims represent care from an average of 1,021 patients per county, but the data come from only 1.6 million unique patients since the average patient is treated by providers in two counties each year. There are no noticeable differences in average patient health (measured by number of Elixhauser comorbidities) or demographics across the three groups of counties.

C.2 GMM Estimates

Medicare periodically updates its geographic adjustments as it obtains new information on local input costs.[44] These updates could bias our reduced-form estimates if they are correlated with the consolidation-induced price shocks and we fail to control for them. To confirm that the updates are not biasing our results, we explicitly use our price shocks as instruments within a Generalized Method of Moments (GMM) framework. For this estimation, we group the years in our sample into four categories: the four years prior to the consolidation, and the short-, medium-, and long-run following the consolidation. These groupings are guided by our initial estimates of the year-by-year evolution of care, as revealed in the estimates of β_t from equation (4). We interpret the two years following the consolidation (1997–1998) as the short term, the following two years (1999–2000) as the medium term, and the following four years (2001–2005) as the long run. We can then model the impact of the consolidation on prices as:

$$
\begin{aligned}
\text{Actual change}_{i,Time} \times Time_t = &\sum_{t \neq 1996} \alpha_t^{Time} \cdot \text{Price change}_i \times I_t \\
&+ \sum_{t \neq 1996} \zeta_t^{Time} \cdot \ln(1990 \text{ pop.}_i) \times I_t \\
&+ \gamma_i^{Time} + \delta_t^{Time} + \eta_{s(i),t}^{Time} + \zeta^{Time\prime} X_{i,s(i),t} + u_{i,s(i),t}^{Time},
\end{aligned}
\tag{15}
$$

where

$$Time \in \{\text{Short-Run, Medium-Run, Long-Run}\}.$$

---

[44]A single interaction between the price change and years after the consolidation explains 65 percent of the county-level variation in GAF during our sample, after controlling for county and state-by-year fixed effects. A regression of county-level GAF on this same interaction variable yields an extremely significant coefficient of 0.87.

Three equations of the form given in equation (15)—for the short-run, medium-run, and long-run post-consolidation time periods, respectively—constitute our model for the impact of the consolidation on prices. We estimate these three sets of coefficients while simultaneously modeling the impact of changing prices on health care quantity. We assume that this effect has the form:

$$
\begin{aligned}
\ln(\text{RVUs}_{i,s(i),t}) = {} & \beta^S \cdot \text{Actual change}_{i,\text{Short-Run}} \times \text{Short-Run}_t \\
& + \beta^M \cdot \text{Actual change}_{i,\text{Medium-Run}} \times \text{Medium-Run}_t \\
& + \beta^L \cdot \text{Actual change}_{i,\text{Long-Run}} \times \text{Long-Run}_t + \sum_{t \neq 1996} \zeta_t^{\text{Supply}} \cdot \ln(1990 \text{ pop.}_i) \times I_t \\
& + \gamma_i^{\text{Supply}} + \delta_t^{\text{Supply}} + \eta_{s(i),t}^{\text{Supply}} + \zeta^{\text{Supply}\prime} X_{i,s(i),t} + \varepsilon_{i,s(i),t}^{\text{Supply}}. \quad (16)
\end{aligned}
$$

By assuming that the price changes are orthogonal to the supply residuals, $\varepsilon_{i,s(i),t}^{\text{Supply}}$, we can jointly estimate this system of equations (15) and (16) through GMM. We use a weighting matrix that accounts for arbitrary correlations within clusters by pre-consolidation payment region. Our results are extremely similar between the OLS and GMM estimations.

C.3   Definition of Elective Procedures

We define elective procedures to include minor procedures, ambulatory procedures, eye procedures, orthopedic procedures, and imaging procedures, in particular the following Betos codes:

- P2A: Major procedure, cardiovascular—CABG
- P2C: Major Procedure, cardiovascular—Thromboendarterectomy
- P2D: Major procedure, cardiovascular—Coronary angioplasty (PTCA)
- P3B: Major procedure, orthopedic—Hip replacement
- P3C: Major procedure, orthopedic—Knee replacement
- P4B: Eye procedure—cataract removal/lens insertion
- P5A: Ambulatory procedures—skin
- P5B: Ambulatory procedures—musculoskeletal
- P6A: Minor procedures—skin
- P6B: Minor procedures—musculoskeletal
- P8A: Endoscopy—arthroscopy
- P8B: Endoscopy—upper gastrointestinal
- P8C: Endoscopy—sigmoidoscopy
- P8D: Endoscopy—colonoscopy
- P8E: Endoscopy—cystoscopy

- P8F: Endoscopy—bronchoscopy
- P8G: Endoscopy—laparoscopic cholecystectomy
- P8H: Endoscopy—laryngoscopy
- I4A: Imaging/procedure—heart including cardiac catheter

Other procedures are defined to include the following Betos categories:

- P1A: Major procedure—breast
- P1B: Major procedure—colectomy
- P1C: Major procedure—cholecystectomy
- P1D: Major procedure—turp
- P1E: Major procedure—hysterctomy
- P1F: Major procedure—explor/decompr/excis disc
- P1G: Major procedure—Other
- P2B: Major procedure, cardiovascular-Aneurysm repair
- P3A: Major procedure, orthopedic—Hip fracture repair
- P4A: Eye procedure—corneal transplant
- P4C: Eye procedure—retinal detachment
- P5C: Ambulatory procedures—groin hernia repair
- P7A: Oncology—radiation therapy
- P7B: Oncology—other
- P9A: Dialysis services

C.4   Identifying Physician-Owned MRIs

We identify physician-owned MRIs as outlined in section 5.2. We define MRIs of the head/neck and other regions using Betos categories I2C and I2D, respectively. Medicare uses the same *CPT* code to represent performing the MRI ("technical component") and reading the image ("professional component"). We require that the claim either indicates the technical component of the service, or alternatively is a "global" bill (encompassing both the technical and professional components).

Specialty codes are listed at `http://www.resdac.org/ddvib/Files/HCFA_PRVDR_SPCLTY_TB.htm` (accessed October 16, 2011). Because we use only a 5 percent sample of claims, while Baker (2010) uses a larger 20 percent file, we depart from his methodology in not requiring a certain number of claims before considering a physician to be an MRI machine owner.

D Protocol for Following Patients in Specific Cohorts

D.1 Identifying Patients with Specified Diagnoses

In order to study the health care provided to comparable groups of patients across space and time, we identify cohorts of patients diagnosed with particular chronic conditions at a given time. We identify patients based on the diagnoses associated with claims filed in 5 percent sample of Medicare Part B beneficiaries discussed in section 2.2. These patients are organized into cohorts based on the year and location in which they appear to have been diagnosed, as defined based on their first claim including one of the diagnoses specified below.

D.1.1 Cardiac Diagnoses

Cardiovascular disease comes in many forms, which result from different problems with the heart muscle. Coronary artery disease (CAD) occurs when plaque accumulates inside the coronary arteries (the arteries that supply blood to the heart muscle). The plaque buildup results in narrowing of these arteries, which can lead to angina (chest pains), deteriorating cardiac function and arrhythmias. Sufficient narrowing can ultimately occlude these arteries, leading to acute myocardial infarction (AMI, or heart attack).

Congestive heart failure (CHF) is a separate type of cardiovascular disease, associated with poor cardiac function. It occurs when the heart is unable to pump sufficient blood throughout the body, and leads to fatigue, shortness of breath, and fluid buildup in the extremities. CHF is often caused in part by CAD, and both diseases are associated with a variety of risk factors. Obesity, diabetes, smoking, hypertension, high cholesterol (hypercholesterolemia) and fat levels (hyperlipidemia) are all associated with the development of both CAD and CHF. Because of the substantial overlap between patients with CAD and CHF, we initially study them together, along with Medicare beneficiaries with any of these risk factors. We then separate out those with differing manifestations of heart disease: those who have had an AMI (and therefore undoubtedly have CAD), those who have a specific diagnosis (CAD or CHF), and those who have some chance of having cardiovascular disease (due to a diagnosis for one of the risk factors), and examine the impact of price shocks on treatment patterns for these distinct cohorts.

There is substantial overlap in the treatments for CAD, CHF, angina, patients who have experienced an AMI, and those in the broader category

at risk for heart disease. We therefore group them together, based on the following ICD-9 diagnoses, some of which benefit from input from Elixhauser et al. (1998). The conditions specified below are not necessarily mutually exclusive, and we will subsequently describe how we identify non-overlapping cohorts from these groups.

- Acute myocardial infarction (AMI) (410)
- Angina: Intermediate coronary syndrome (411.1) and angina pectoris (413)
- Coronary artery disease (CAD) (410–414)
- Congestive heart failure (CHF) (428)
- Chest pain (786.5)
- Hypertension (401.1, 401.9, 402.10, 402.90, 404.10, 404.90, 405.11, 405.19, 405.91, 405.99)
- Arrhythmia (426.10, 426.11, 426.13, 426.2, 426.3, 426.4, 426.51, 426.52, 426.53, 426.6, 426.7, 426.8, 427.0, 427.2, 427.31, 427.60, 427.9, 785.0, V450, V533)
- Diabetes (250)
- At risk for heart disease: chest pain, hypertension, arrhythmia, diabetes, hypercholesterolemia (272.0), hyperglyceridemia (272.1), hyperlipidemia (272.2, 272.4), hyperchylomicronemia (272.3)
- Broadest cardiac cohort: all of the above

We use some of these conditions as exclusion criteria for other cohorts as follows. We exclude patients with a prior AMI from both the CAD and CHF cohorts. We exclude patients with a prior diagnosis in any of these three categories (AMI, CAD, CHF) from the "heart disease risk" cohort.

D.1.2 Back Pain Diagnoses

For these purposes, we use the following list of ICD-9 codes as back pain diagnoses, following Cherkin et al. (1992):

- Dorsopathies (720–724)
- Psychalgia (307.89)
- Sprains and strains of sacroiliac region (846)
- Sprains and strains of other and unspecified parts of back: Lumbar (847.2), Sacrum (847.3), and Unspecified site of back (847.9)
- Anomaly of spine, unspecified (756.10)
- Absence of vertebra, congenital (756.13)

- Anomalies of spine: other (756.19)

Also following Cherkin et al. (1992), we exclude any of the above claims that also record one of the following diagnoses. Patients with these concurrent diagnoses are likely to have back pain with a more specific cause than those with only the diagnoses listed above. These conditions potentially indicate different treatments, so our analysis of back pain treatments may be less appropriate for patients with the following comorbidities:

- Neoplasms (140–239)
- Intraspinal abscess (324.1)
- Inflammatory spondyloarthropathies (720)
- Osteomyelitis (730)
- Vertebral fractures with or without spinal cord injury (805–806)
- Vertebral dislocations (839)
- External causes of injury and poisoning (E-codes)

D.1.3   Diabetes Diagnosis

Patients with diabetes are diagnosed using only the ICD-9 code for diabetes, 250.

D.2   Outcomes of Interest for Patients with Specific Conditions

Once we have identified the cohorts of patients who meet criteria 1 and/or 2 in section D.1, we locate all of their claims in the carrier files for the two years following the date of diagnosis. All of the outcomes based on these claims are assigned to the cohort in which the patient initially appeared with the diagnosis. Regardless of whether the patient moved or saw health care providers in different locations at any time after we first observe the diagnosis, the cohort assignment remains unchanged.

Maintaining the cohorts over time enables us to avoid any bias induced by which follow-up care patients receive after their initial diagnosis. It is extremely likely that, depending on initial characteristics of the diagnosis— such as the location, time, or applicable reimbursement rate—patients would receive follow-up care from different providers. For instance, patients may be more likely to see orthopedic specialists after reimbursement rates have increased in their home region, even if the orthopedists are located in a different region. If we assigned this decision to the region where the orthopedist is located, we would induce a bias based on the price difference between the

location of diagnosis and the specialist's location. To avoid this, we evaluate all of the care received by a patient in a particular diagnostic cohort together, using only information from the time of diagnosis. This is likely to mute our results, since some patients in diagnosis cohorts with different reimbursement rates are likely to receive follow-up care (specialists, images, laboratories, etc.) from the same providers.

The outcomes of interest are defined based on the Medicare billing code in the subsequent claims. The relevant billing codes are those listed below, based on the *Current Procedural Terminology* coding system (American Medical Association, 1992–2005). This is the coding system used for Medicare reimbursement of carrier claims.[45] We calculate separate variables indicating whether each service were provided within one year or two years of diagnosis. Section D.2.3 presents codes for evaluation and management services that we measure for all of the patient cohorts.

D.2.1   Outcomes of Interest for Cardiac Patients

We examine the following set of outcomes for the various heart disease cohorts, as defined in section D.1.1.

- Left heart catheterization: 93511–93529, 93571, 93572
- Right heart catheterization: 93501, 93503, 93508, 93526, 93527, 93528, 93529, 93561, 93562
- Right or left heart catheterization
- Stent: 92980–92989
- Any catheterization: right or left heart catheterization, or stent
- Stress test: 93015, 93016, 93017, 93018, 78460
- Nuclear imaging: 78460, 78472, 78473
- Echocardiogram: 93300–93350
- Coronary artery bypass graft: 33500–33545

D.2.2   Outcomes of Interest for Back Pain Patients

For patients in our back pain cohorts, as defined in section D.1.2, we measure the following outcomes, following Weiner et al. (2006) for guidance:

- Physical therapy: 97001–98999

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[45]Medicare's implementation of the CPT, together with the Relative Value Units assigned to each service, is is provided by CMS at `http://www.cms.gov/PhysicianFeeSched/01_overview.asp` (accessed October 16, 2011).

- CAT scan: 72131, 72132, 72133
- MRI: 72148, 72149
- X-ray: 72100–72120
- Advanced imaging: MRI or CAT scan
- All imaging: X-ray, MRI, or CAT scan
- Myelogram or chemonucleolysis: 72265, 72270, 62292
- Open diskectomy: 63071–63079
- Percutaneous diskectomy: 62287
- Laminectomy or laminotomy: 63005, 63017, 63030, 63042, 63047
- Arthrodesis (spinal fusion): 22630
- Facet lumbar or sacral injection: 64475, 64476, 64442, 64443
- Other injection: 62311, 64483, 64484, 27096, 62289
- Any injection: Facet lumbar, sacral, or other injection

Arthrodesis involves fusing two vertebra together to inhibit motion that might be the source of pain. Diskectomy is the removal of part of an intervertebral disk, which may be herniated and causing pain by exerting pressure on a nerve. A laminectomy involves the excision of part of a vertebra (the lamina), and in a laminotomy only part of the lamina is removed.

D.2.3 Outcomes of Interest for All Patients

For all patients in the various cohorts defined in section D.1, we measure the following outcomes:

- Outpatient evaluation and management: 99201–99205, 99211–99215, 99241–99245, 99271–99275, 99381–99397, 99401–99429
- Inpatient evaluation and management: 99217–99239, 99251–99263, 99281–99289
- Any evaluation and management: Outpatient evaluation and management, inpatient evaluation and management

E   Robustness and Additional Decompositions

E.1   Robustness of Aggregate Results

Appendix Table E.1 shows that the baseline results in Table 2 are not sensitive to our matching procedure or the steps we have taken to reduce the possible influence of outlier observations. Appendix Table E.2 repeats these

regressions using the GMM procedure described in equations (15) and (16), and finds very similar results.

To confirm the significance of our estimates and alleviate any concern that our clustered standard errors might be biased downward, we run a permutation test on our baseline regression. We randomly allocate our price shocks across counties and repeat our estimation 2,000 times to obtain a placebo distribution of the long-run effect of prices on care provision, which is displayed in Appendix Figure E.3. The figure shows that our actual estimate, indicated with the dashed vertical line, lies in the top 1 percent of the empirical distribution of placebo estimates, indicating that it is statistically different from zero with $p < 0.01$. We similarly find that $p < 0.01$ for the medium-run coefficient, and $p < 0.05$ for the short-run coefficient.

E.2   Providers Treating Medicare Patients

The decision of where to locate and what types of patients to treat are likely to be some of the most significant a physician makes. We observe the results of these decisions by virtue of which providers show up in our sample of claims. Appendix Table E.3 decomposes our aggregate care results into the total number of physicians and RVUs per physician. In columns 1 through 3 we measure total care provision in an area, and control for the log number of patients treated. Because the outcome variables are expressed in logs, the coefficients in columns 2 and 3 nearly, but do not exactly, add up to that on total RVUs in an area, which is shown in column 1. Columns 4 through 6 repeat this decomposition expressing outcome variables as per-patient quantities.

The results imply that the response to reimbursement rates comes predominantly through the number of physicians per patient, which can be viewed as an extensive response margin. It is important to note that this does not imply that physicians are moving across county borders, which might be an unrealistic margin for short-run supply responses. Additional physicians only appear in our data when they provide care to the beneficiaries in the sample. Hence an expansion of the network of providers servicing the individuals in our 5 percent sample of beneficiaries would produce this result.[46] The result provides evidence that increases in care provision are not coming exclusively through additional visits to the patients' existing physicians. An increasing use of multiple physicians (whether through entry of providers into the Medicare market or through referrals to specialists) is an essential feature of the

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[46]Appendix E.3 discusses a correction we make to account for the influence of sampling error on the number of providers we observe. This correction has only a minimal effect on the results reported here.

response.

To directly examine movement across borders, column 7 looks at the effect of reimbursement rates on the tendency of patients to cross borders when obtaining care. We assign patients to a Medicare Payment Locality based on where they live, using the locality definitions from 1996. The outcome variable captures the share of care provided in area i that is delivered to patients living in other areas. In both Panels A and B, the price change has no significant effect on this variable. The negative sign on the point estimate is the opposite of what one would expect if patients were crossing Payment Locality borders to see providers in better-reimbursed areas. This suggests that our baseline estimates do not result from border crossing but instead reflect changes in the care patients ultimately receive. This conclusion is consistent with the patient-level evidence, where we found that individual patients receive different treatments based on the prevailing reimbursement rates at the time of diagnosis.

Appendix Table E.4 presents elasticities of care provision with respect to reimbursement rates across distinct provider types, focusing on general practitioners, specialists, surgeons, and health care providers who are not physicians (e.g., physical therapists). We observe large responses among each of the provider types. The evidence is particularly strong in the case of general practitioners, who are associated with long-run elasticities on the order of 3. Strong responses among general practitioners are consistent with their role as gatekeepers to specialists. The response of specialists appears to be roughly in line with the baseline results in both specifications. Short and medium run responses appear to be weakest among surgeons, although their long run response is similar in magnitude to the estimates associated with specialists.

E.3 Estimating Provider Numbers from a Sample of Claims

Our empirical analysis beginning in section 3 relies on a 5 percent sample of Medicare claims data, as described in section 2.2. While these data should yield consistent estimates of aggregate outcomes, such as total health care supply, and patient-level outcomes, such as probabilities of receiving particular treatments, they may not immediately offer consistent estimates along other dimensions of health care supply.

In particular, the 5 percent sample can provide a biased count of the number of providers serving the Medicare market. In a large area, a random sample of patients is likely to include those who have received care from most or all of the providers available in that market. Since the claims data include provider

identifiers, we can simply count the number of unique identifiers serving patients in such a region and have an accurate count of their number. In a smaller county, however, the noise in individual patients' choice of physician is more likely to lead us to never observe some of the area's providers.

These omissions are not independently distributed across areas; instead, they are likely to be correlated with the number of patients receiving care in a particular county. Since these numbers in turn are correlated with the reimbursement rate shocks (as discussed in Appendix B.1), this noise has the potential to lead to biased estimates of the impact of price changes on outcomes related to provider counts (in particular, the number of providers treating Medicare patients in an area, and care supplied per provider).

In order to account for the possible omission of providers from the sample of claims data in some areas, we implement a simple correction to compute an implied number of providers consistent with the number observed in the claims data. This correction still only estimates the number of providers serving Medicare patients, and does not convey information about the area's non-Medicare health care supply. It is intended to approximate the number of providers we would observe in a dataset containing 100 percent of the Medicare claims for each county in each year.

Suppose that area i has D_{it} providers serving Medicare patients in year t, and a sample of N_{it} patients in this area show up in the 5 percent sample of claims data. We assume that each time a patient sees a new provider, the provider is chosen independently with each provider having an equal probability of being chosen. This assumption is certainly counterfactual, since referal networks and relationships between medical practices undoubtedly induce correlations of provider choice across patients. Nevertheless, it is a reasonable first approximation and it yields a readily implementable result. In particular, the expected number of providers observed in the claims data for this area is then

$$\text{Expected number of providers in the data} = D_{it} \cdot \left[1 - \left(1 - \frac{1}{D_{it}} \right)^{N_{it}} \right]. \quad (17)$$

By counting the number of providers in our claims sample located in area i we obtain an empirical measure of the left-hand side of equation (17). Since we also observe N_{it} we can solve equation (17) numerically for D_{it}. We can then use the resulting estimate of D_{it} in place of the actual provider count and replicate our analyses of how the price change influences the two margins related to provider counts.

When we do so, we find that the results remain virtually unchanged. Thus our estimates of the impact of reimbursement rate changes on the provider

margins were not significantly biased by the omission of providers due to the nature of our claims data sample.

E.4   Decomposition of Care

Appendix Table E.5 presents additional decompositions of the baseline specification in column 1 of Appendix Table 2. Column 1 begins by estimating the effect of changes reimbursement rates on the revenue received by physicians from serving Medicare beneficiaries. The elasticities in column 1 are roughly equal to one plus the elasticities from Appendix Table 2. The long run elasticities of Medicare revenues with respect to reimbursement rates are on the order of 3 or 4. This result is evidence against a strong form of the income targeting hypothesis, in which physicians offset changes in Medicare reimbursement rates by adjusting service volumes so as to maintain a constant stream of Medicare revenues.[47]

That the revenue elasticity is approximately equal to one plus the quantity elasticity is not surprising, but was not guaranteed. As detailed in Appendix B.1, total RVUs is the sum of work RVUs, practice expense RVUs, and malpractice expense RVUs, each of which has its own geographically-determined price index (Geographic Practice Cost Index). The consolidation of Payment Localities affected these indices differently, with the largest changes typically taking place within the practice expense component. A major shift in the mix of services towards services that are intensive in terms of practice RVUs would have led the revenue elasticity to exceed the quantity elasticity by more than one. Furthermore, the hypothesis of a large income effect would suggest that work RVUs, which represent the physician's own time and effort, might exhibit a weaker response than practice expense RVUs and could even respond negatively to price shocks.

Columns 2 through 4 of Appendix Table E.5 report estimates of the elasticity of the three RVU types with respect to the change in the total geographic adjustment factor. The elasticity estimates are statistically and economically indistinguishable across the RVU types. Consistent with the revenue elasticity being one greater than the quantity elasticity, the results suggest that the consolidation of payment localities did not significantly alter the mix of services in a manner skewed towards practice expense RVUs.

Appendix Table E.6 tests for differential responses in health care or mortality by age group. Columns 1 through 3 split health care provision by the patient's age, grouped into those 65 to 74 years old, 75 to 84, and 85 or above.

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[47]In section 6.1, we explore whether physicians change their supply of care to non-Medicare patients in response to a change in Medicare's reimbursement rates.

We find somewhat larger price responses among the younger group, although care for all three exhibits a strong positive response to prices. We next look at each group's mortality rate. The dependent variable in these regressions is the fraction of beneficiaries residing in a county who die during a given calendar year, as recorded in the Denominator files. If the extra care that beneficiaries are receiving in areas with a positive price shock contributes to survival, we should see a negative effect of the price change on mortality.

The results in columns 4 through 6 show no significant effect of prices on mortality. The long-run point estimates indicate that each percentage point increase in prices reduces mortality by 0.01 percentage points for the youngest age group, by 0.015 percentage points for the middle age group, and increases mortality for the oldest group. None of these coefficients is statistically significant, and even the lowest point within the 95 percent confidence interval—a mortality decline of 0.05 percentage points—would not be cost-effective at conventional values of a life-year (Cutler, Rosen and Vijan, 2006).

We measure the effects of reimbursement rate shocks on other health outcomes in Appendix Table E.7. This table uses data from the Behavioral Risk Factor Surveillance System, which is a national survey conducted annually by the Centers for Disease Control and Prevention. We use data on respondents aged 65 years or over, almost all of whom receive Medicare and are thus affected by the consolidation-induced price shocks. Our sample size grows from 11,000 responses in 1993 to 73,000 by 2005.

We find no effect of price changes on any measure of health status or the probability that the patient has received an influenza or pneumococcal vaccine. The estimates are not extremely precise; at the lowest bounds of the 95 percent confidence intervals, a 2 percent price change moves most of the dependent variables by about 10 percent of a standard deviation.

E.5 Differential Supply Responses Across Areas

If physicians have strong preferences for reaching a specific income target, price elasticities may be different—and even of opposite signs—in counties with positive and negative price shocks. In Appendix Table E.8, we look at the effect of reimbursement shocks within different price ranges. We replace the continuous price change measure with four indicator variables for different ranges of the GAF change. The first coefficient shows an interaction between an indicator for years after the consolidation and an indicator for areas with a GAF change below -0.03. We look separately at areas with GAF changes from -0.015 to -0.03, and equal ranges on the positive side, omitting areas with small changes (those where $-0.015 < \text{Price change}_i < 0.015$). We then

interact these variables with indicators for the short-, medium-, and long-run periods after the consolidation.

The coefficients on the twelve resulting interactions are shown in Appendix Table E.8. Columns 1 and 2 examine their impact on aggregate health care supply. Within each time period, the coefficients generally increase from the most negative range of shocks to the most positive, suggesting an approximately linear response to price changes, but they are not very precisely measured.

The target income hypothesis follows from assumptions about individual provider behavior, so columns 3 and 4 decompose the total health care supply into two margins: the impact of prices on the number of providers and average supply per provider. Once again, the estimates are noisy, so these estimates do not provide a precise test of individual provider behavior. Columns 5 and 6 decompose aggregate supply along a different margin, number of services and service intensity. Estimates are imprecise, but the coefficients generally point in the direction of positively sloped responses along both margins.

Target income should be more relevant for physicians who were treating patients before the price change and hence have a target to match. We study this group by limiting the data to providers who filed a claim in our sample before 1996. Appendix Table E.9 reports a positive supply response for this sample just as for the overall results. Both the number of providers and average care respond positively to prices, rejecting the hypothesis of strong income effects.

We ask whether income effects are predominant among areas experiencing a negative shock by testing for nonlinearities in the sample. Columns 4 through 6 show similar regressions, but interacting the area's price change category with an indicator for years following the consolidation. These estimates, while noisy, tend to confirm the results of columns 1 through 3 that coefficients are larger for more positively shocked areas.

In Appendix Table E.10, we examine the robustness of our results to area-level controls and across different types of counties. In columns 1 and 2 we report aggregate supply responses, controlling for time-varying impacts of being in a metropolitan area (separate interactions between metropolitan status and dummies for each year).[48] The baseline results from Table 2 are robust to these controls. In columns 3 through 6, we run separate estimates for counties in a metropolitan area and rural counties. Supply responses are positive for both groups of counties, though larger in metropolitan counties and indistin-

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[48]We use the 1999 metropolitan area definitions issued by the Office of Management and Budget, including all counties in a New England Consolidated Metropolitan Area as well as traditional Metropolitan Statistical Areas.

guishable from zero in nonmetropolitan ones. Finally, columns 7 and 8 report the baseline specification controlling for annual data on log personal income, and find minimal effect on the estimates.

E.6 Treatments for Additional Cohorts

Theory predicts that supply elasticities will be small for services that are relevant, and associated with large benefits, for clearly defined populations. We test this prediction by looking at care for beneficiaries diagnosed with hip fractures. In columns 1 through 3 of Appendix Table E.12 we estimate the effect of price changes on the provision of fracture-specific treatments and general office visits to these beneficiaries. Column 1 shows that, as theory predicts, fracture-specific treatments do not respond to prices. Columns 2 and 3 show that general office visits exhibit substantial price responsiveness (estimated in levels and logs respectively). Columns 4 and 5 report the effect of prices on the broader packages of care received by these patients, with imprecise results in both instances.

In Appendix Table E.13 we measure the response of the same services for patients who entered our cohorts due to a myocardial infarction (MI, or heart attack). This cohort contains 226,388 patients, who are treated much more intensively than the broader cardiovascular disease cohort; 32 percent receive a catheterization and 7 percent a stent. For this sub-group, the implied elasticities for intensive procedures and office visits are similar to those for the full cohort, while the elasticities for testing and imaging services are smaller.

We next look at outcomes for diabetics. Their overall care responds with a similar magnitude as that for cardiac patients, but Appendix Table E.14 shows that evidence of health gains is again elusive. This table runs regressions looking at hospitalizations for three ailments commonly caused by diabetes: strokes (Panel A), MI (Panel B), and renal failure (Panel C). We find no evidence of significant reductions in hospitalizations within 4 years of entering the cohort.

Appendix Figure E.1: **Distribution of Consolidation-Induced Price Shocks**

Panel A: Relationship with County Population

GAFchg = -0.0041(0.00019)*lpop90 + 0.056(0.0024) + controls. Partial R^2=0.14, N=2916
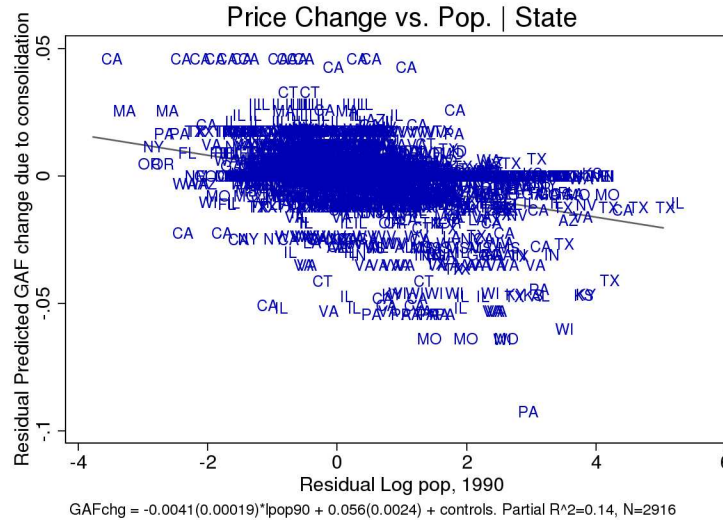
Panel B: Overall Distribution
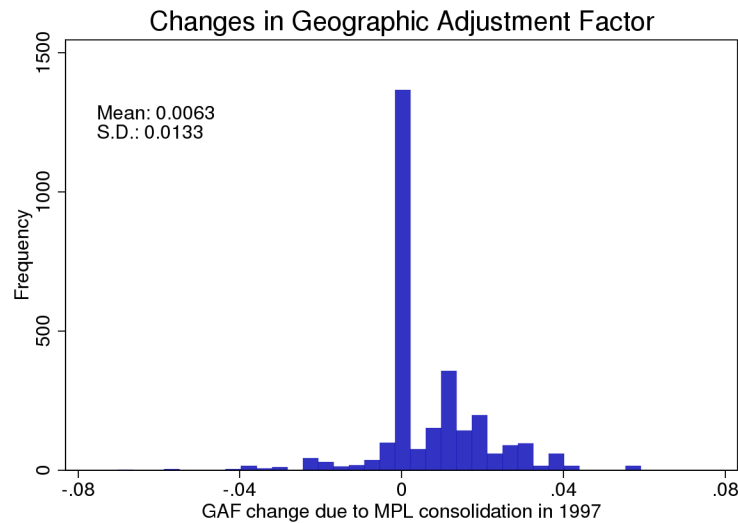
Panel A shows the relationship between the county-level changes in Geographic Adjustment Factor (GAF) from Figure 2 and county log population as of 1990, after controlling for state fixed effects. Each county is denoted by the abbreviation for its state. Panel B shows the distribution of these county-level changes. Weighted by the amount of care there was no change on average, but the county-level mean in this (unweighted) histogram is positive because lower-cost counties are more numerous. Sources: Price change: *Federal Register*, various issues; county population: U.S. Census.

Appendix Figure E.2: Annual Coefficients on Log County Population Controls
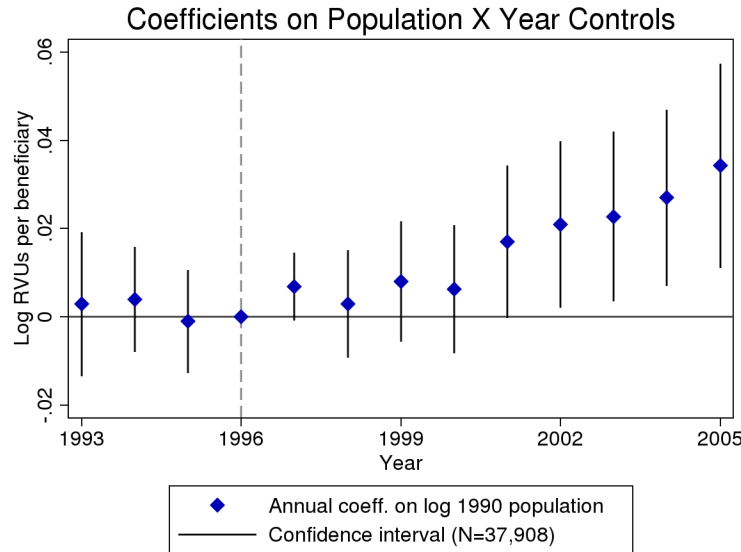
These graphs show coefficients and associated standard errors for population-by-year control variables from ordinary least squares regressions in which log health care quantity supplied per Medicare patient is the dependent variable. This quantity, measured for each of 2,916 counties and in each year 1993–2005, is regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicator variables for each year. The coefficients correspond to the ζ_t parameters in equation (4), which multiply a set of year dummy variables interacted with the log of each county's 1990 population. This specification, which is the same one whose coefficients β_t on annual indicators with the reimbursement rate shocks are shown in Panel A of Figure 3, also controls for county fixed effects, state-by-year effects, the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Figure E.3: Distribution of Placebo Estimates From Permutation Test
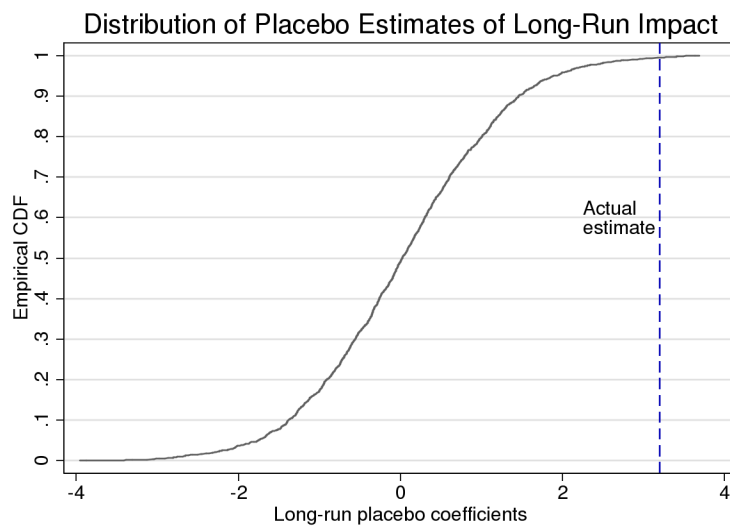
This graph shows the empirical distribution of placebo coefficients on the interaction of the reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997 with an indicator for the long-run years following the consolidation (2001 through 2005). The baseline regression, in which log health care quantity supplied per Medicare patient is the dependent variable, is run 2,000 times with the reimbursement rate shocks randomly assigned to counties in each iteration. These shocks are interacted with three indicators for year groups (1997–1998, 1999–2000, and 2001–2005). All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. They also control for the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). The empirical distribution on the long-run post-consolidation interaction (2001–2005) is shown in the figure, and the dashed vertical line indicates the actual empirical estimate of this coefficient. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.1: **Effect of Reimbursement Rate on Log Health Care Per Patient: OLS Estimates**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample		No Winsorizing		No Demographics		Equal Weights	
Price change × Short run	1.186*	0.757	1.241*	0.740	1.222*	0.753	0.748	0.498
	(0.490)	(0.517)	(0.495)	(0.528)	(0.525)	(0.506)	(0.569)	(0.537)
Price change × Medium run	2.227**	1.508*	2.290**	1.450*	2.253**	1.466*	2.047**	1.631*
	(0.592)	(0.683)	(0.593)	(0.705)	(0.626)	(0.643)	(0.689)	(0.654)
Price change × Long run	3.088**	1.857+	3.179**	1.742+	3.163**	1.816*	2.100**	1.393+
	(0.942)	(0.950)	(0.955)	(0.992)	(1.019)	(0.909)	(0.772)	(0.806)
Price change × Linear Time Trend		0.145		0.169		0.158		0.0832
		(0.114)		(0.122)		(0.113)		(0.130)
Observations	37,908	37,908	37,908	37,908	37,908	37,908	37,908	37,908
1% Winsorized?	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Demographic controls?	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Patient weights?	Yes	Yes	Yes	Yes	Yes	Yes	No	No

**p < 0.01, *p < 0.05, +p < 0.1. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient is the dependent variable. This quantity, measured for each of 2,916 counties and in each year 1993–2005, is regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. The demographic and health-based control variables are the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.2:   **Effect of Reimbursement Rate on Log Health Care Per Patient: GMM Estimates**

	(1) Baseline	(2) Baseline	(3) No Wins.	(4) No Wins.	(5) No Demogs.	(6) No Demogs.	(7) Unweighted	(8) Unweighted
Short-run	0.878*	0.513	0.949*	0.548	0.566	0.329	0.979+	0.871+
Price change	(0.415)	(0.344)	(0.426)	(0.358)	(0.421)	(0.357)	(0.542)	(0.481)
Medium-run	2.018**	1.283**	2.079**	1.261*	1.560*	1.003+	2.375**	2.155**
Price change	(0.658)	(0.491)	(0.664)	(0.502)	(0.659)	(0.515)	(0.674)	(0.574)
Long-run	3.520**	1.834**	3.589**	1.698**	2.763**	1.436*	2.516**	2.294**
Price change	(1.080)	(0.537)	(1.097)	(0.568)	(1.059)	(0.581)	(0.777)	(0.565)
Observations	37,908	37,908	37,908	37,908	37,908	37,908	37,908	37,908
Trend in shock	No	Yes	No	Yes	No	Yes	No	Yes
1% Winsorized?	Yes	Yes	No	No	Yes	Yes	Yes	Yes
Demographic controls?	Yes	Yes	Yes	Yes	No	No	Yes	Yes
Patient weights?	Yes	Yes	Yes	Yes	Yes	Yes	No	No

**p < 0.01, *p < 0.05, +p < 0.1. This table reports coefficients from estimating the impact of prices on health care supply with the Generalized Method of Moments, across 2,916 counties and in each year 1993–2005. Log health care quantity supplied per Medicare patient is the dependent variable. As shown in equations equations (15) and (16) in the text, this system uses shocks to reimbursement rates resulting from the consolidation of Medicare's fee schedule areas in 1997, interacted with indicators for time after the consolidation, to identify price variation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications includes controls for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. The demographic and health-based control variables are the fraction of the county's sample beneficiary pool aged 65–59, 70- -74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.3: Effect of Reimbursement Rate on Number of Providers

Outcome:	(1) Total RVUs	(2) RVUs per Physician	(3) Total Physicians	(4) RVUs per Patient	(5) RVUs Per Physician	(6) Physicians Per Patient	(7) Out-of-Area Patient Share
Price change × Short-run Post-consolidation	0.70 (0.40)	0.06 (0.28)	0.64** (0.27)	1.186* (0.490)	-0.120 (0.262)	1.281** (0.415)	-0.016 (0.087)
Price change × Medium-run Post-consolidation	1.47** (0.49)	0.56 (0.36)	0.91** (0.34)	2.227** (0.592)	0.253 (0.338)	1.953** (0.553)	-0.198 (0.132)
Price change × Long-run Post-consolidation	2.32** (0.83)	0.94 (0.52)	1.36** (0.48)	3.088** (0.942)	0.432 (0.431)	2.529** (0.740)	-0.179 (0.172)
Control for log num. patients	Yes	Yes	Yes	No	No	No	No

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which various aspects of log health care quantity supplied to all Medicare patients treated in the county (columns 1–3), log quantity of care per Medicare patient treated in the county (columns 4–6), or the share of treatments supplied to patients residing in a different Medicare fee schedule area (according to the 1996 definitions) is the dependent variable. These quantities, measured for each of 2,916 counties and in each year 1993–2005 (so $N = 37,908$), are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. All dependent variables are in natural logs. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. Columns 1–3 also control for the log number of patients treated in the county. All specifications also control for the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.4: **Effect of Reimbursement Rate on Health Care by Provider Type**

Provider Category:	(1) General Practitioners	(2) Specialists	(3) Surgeons	(4) Non-MD Specialists
Price change × Short-run Post-consolidation	1.217* (0.484)	1.677** (0.527)	0.931 (0.588)	1.338 (0.972)
Price change × Medium-run Post-consolidation	2.490** (0.691)	2.653** (0.631)	1.750* (0.677)	2.454+ (1.252)
Price change × Long-run Post-consolidation	2.919** (1.005)	3.375** (0.953)	2.938** (0.936)	2.461+ (1.483)
Observations	37,554	32,067	28,587	35,773

**p < 0.01, *p < 0.05, +p < 0.1. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient by each category of provider is the dependent variable. These quantities, measured for each county and in each year 1993–2005, are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. They also control for the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.5: **Effect of Reimbursement Rate on Log Health Care by Nature of Service**

Outcome:	(1) Medicare Revenues	(2) Practice Expense Units	(3) Physician Work Units	(4) Malpractice Expense Units
Price change ×	2.224**	1.224*	1.137*	1.249*
Short-run Post-consolidation	(0.513)	(0.491)	(0.491)	(0.520)
Price change ×	3.250**	2.341**	2.118**	2.276**
Medium-run Post-consolidation	(0.609)	(0.613)	(0.579)	(0.601)
Price change ×	4.096**	3.454**	2.765**	3.232**
Long-run Post-consolidation	(0.970)	(1.029)	(0.885)	(0.930)

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which various aspects of log health care quantity supplied per Medicare patient are the dependent variables. These quantities, measured for each of 2,916 counties and in each year 1993–2005 (so $N = 37,908$), are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. All dependent variables are in natural logs. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. They also control for the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.6: **Effect of Reimbursement Rate on Health Care and Mortality by Age Group**

	(1)	(2)	(3)	(4)	(5)	(6)
Outcome:	Quantity of Care Supplied			Annual Beneficiary Mortality		
Age Group:	65–74	75–84	≥ 85	65–74	75–84	≥ 85
Price change ×	1.208*	1.388*	0.657	-0.00215	0.00606	0.0251
Short-run Post-consolidation	(0.530)	(0.646)	(0.552)	(0.00978)	(0.0222)	(0.0597)
Price change ×	2.184**	2.504**	1.544*	-0.0130	-0.0182	-0.0136
Medium-run Post-consolidation	(0.630)	(0.743)	(0.648)	(0.0109)	(0.0141)	(0.0528)
Price change ×	3.428**	3.191**	2.379*	-0.00975	-0.0152	0.0337
Long-run Post-consolidation	(1.064)	(1.107)	(0.986)	(0.00969)	(0.0195)	(0.0323)
Observations	37,206	37,401	36,218	37,206	37,401	36,218

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient in each age group (columns 1–3) or fraction of beneficiares in each age group who die in the year (columns 4–6) is the dependent variable. These quantities, measured for each of 2,916 counties and in each year 1993–2005 (so $N = 37,908$), are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. They also control for the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.7: **Effect of Reimbursement Rate on Self-Reported Health**

Outcome:	(1)	(2)	(3)	(4)	(5)	(6)
	Days in past month:				Received vaccine:	
	In poor physical health?	Kept from activities due to health?	Health status in general	High cholesterol (ever told)?	Influenza in past year?	Pneumococcal ever?
Price change ×	-3.384	-4.752	-0.687	-0.375	-0.205	0.577
Post-consolidation	(5.631)	(7.880)	(0.443)	(0.337)	(0.355)	(0.353)
Sample Mean	5.545	6.096	3.084	0.451	0.658	0.575
Sample Std. Dev.	2.641	4.237	0.325	0.141	0.130	0.168
Observations	9,129	9,094	9,671	6,019	8,034	8,034

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which self-reported health status and indicators for receiving preventative care from the Behavioral Risk Factor Surveillance System (BRFSS) are the dependent variables. These responses, averaged across respondents in each county-by-year cell, are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. Responses for columns 1 and 2 give the number of days out of the past 30 that the respondent was in poor physical health or kept from doing usual activities due to health. "Health status in general," in column 3, is reported on a 1 to 5 scale, where 1 indicates poor health and 5 indicates excellent health. Columns 4 through 6 come from binary indicator variables. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. Sources: Price change: *Federal Register*, various issues; BRFSS data: Centers for Disease Control and Prevention; county population: Census Bureau.

Appendix Table E.8: **Effect of Reimbursement Rate on Health Care by Magnitude of Price Shock**

	(1) Quantity Weighted	(2) Quantity Unweighted	(3) Providers per Patient	(4) RVUs per Provider	(5) Services per Patient	(6) RVUs per Service
Price change < -0.03	-0.0279	0.0107	-0.0394	0.0259	-0.0246	-0.00235
× Short-run Post-consolidation	(0.0334)	(0.0512)	(0.0298)	(0.0242)	(0.0399)	(0.0300)
$-0.03 <$ Price change < -0.015	-0.0778*	-0.0527+	-0.0301+	-0.0328	0.0101	-0.0922**
× Short-run Post-consolidation	(0.0329)	(0.0291)	(0.0179)	(0.0225)	(0.0162)	(0.0310)
$0.015 <$ Price change < 0.035	0.0191	0.0119	0.0103	0.0214	0.0149	0.00742
× Short-run Post-consolidation	(0.0368)	(0.0210)	(0.0211)	(0.0236)	(0.0322)	(0.0276)
$0.035 <$ Price change	0.0158	0.0391	0.0431	-0.0226	0.0313	-0.0121
× Short-run Post-consolidation	(0.0363)	(0.0281)	(0.0266)	(0.0276)	(0.0490)	(0.0388)
Price change < -0.03	-0.0936+	-0.0203	-0.0997*	0.0238	-0.0837+	-0.00807
× Medium-run Post-consolidation	(0.0478)	(0.0502)	(0.0428)	(0.0312)	(0.0451)	(0.0368)
$-0.03 <$ Price change < -0.015	-0.103*	-0.0672+	-0.0418	-0.0422	0.0143	-0.121**
× Medium-run Post-consolidation	(0.0432)	(0.0349)	(0.0349)	(0.0326)	(0.0293)	(0.0341)
$0.015 <$ Price change < 0.035	0.0292	0.0471+	0.00777	0.0337	0.0358	-0.00628
× Medium-run Post-consolidation	(0.0446)	(0.0245)	(0.0308)	(0.0323)	(0.0424)	(0.0322)
$0.035 <$ Price change	0.0556	0.108**	0.00724	0.0594	0.0379	0.0223
× Medium-run Post-consolidation	(0.0385)	(0.0345)	(0.0401)	(0.0410)	(0.0361)	(0.0261)
Price change < -0.03	-0.184*	-0.0518	-0.149**	-0.0161	-0.103+	-0.0790
× Long-run Post-consolidation	(0.0751)	(0.0694)	(0.0546)	(0.0380)	(0.0544)	(0.0519)
$-0.03 <$ Price change < -0.015	-0.0740	-0.0611+	-0.00825	-0.0444	0.0746+	-0.153**
× Long-run Post-consolidation	(0.0554)	(0.0355)	(0.0480)	(0.0372)	(0.0398)	(0.0386)
$0.015 <$ Price change < 0.035	0.0463	0.0708**	0.0326	0.0230	0.0841*	-0.0386
× Long-run Post-consolidation	(0.0516)	(0.0266)	(0.0351)	(0.0339)	(0.0406)	(0.0420)
$0.035 <$ Price change	0.0155	0.0728	-0.0302	0.0493	0.0417	-0.0224
× Long-run Post-consolidation	(0.0576)	(0.0471)	(0.0513)	(0.0589)	(0.0607)	(0.0417)
Observations	37,908	37,908	37,908	37,908	37,908	37,908
Patient weights?	Yes	No	Yes	Yes	Yes	Yes

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient is the dependent variable. These quantities, measured for each county and in each year 1993–2005, are regressed on categories of the reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997. "Short Run" refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. Additional controls and sources are as in Table 2.

Appendix Table E.9: Effect of Reimbursement Rate on Health Care by Incumbent Providers

	(1) Care by Incumbents	(2) Care per Incumbent	(3) Incumbents per Patient	(4) Care by Incumbents	(5) Care per Incumbent	(6) Incumbents per Patient
Price change × Short-run Post-consolidation	0.917 (0.722)	-0.115 (0.469)	0.919+ (0.498)			
Price change × Medium-run Post-consolidation	2.252 (1.650)	1.251 (0.800)	1.826+ (0.999)			
Price change × Long-run Post-consolidation	3.506+ (2.001)	1.869 (1.43)	2.156* (0.947)			
Price change < -0.03 × Post-consolidation				0.07 (0.16)	-0.0003 (0.067)	0.009 (0.086)
$-0.03 <$ Price change < -0.015 × Post-consolidation				0.13 (0.17)	0.041 (0.064)	0.050 (0.083)
$0.015 <$ Price change < 0.035 × Post-consolidation				0.26* (0.13)	0.12* (0.054)	0.104 (0.069)
Price change < 0.035 × Post-consolidation				0.15+ (0.085)	-0.00065 (0.038)	0.123* (0.060)
Observations	37,386	37,386	37,386	37,386	37,386	37,386

**$**p < 0.01$, $*p < 0.05$, $+p < 0.1$. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient by incumbent providers is the dependent variable. Incumbent providers are defined as those appearing in the claims data prior to the consolidation. These quantities, measured for each county and in each year 1993–2005, are regressed on variables derived from the reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. They also control for the fraction of the county's sample beneficiary pool aged 65–59, 70–74, 75–79, and 80–84, the fraction black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and with 2, 3, 4, and 6 or more comorbidities as defined by Elixhauser et al. (1998). Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.10: **Effect of Reimbursement Rate on Health Care by Area Characteristics**

	(1) MSA control	(2) MSA control	(3) Non-MSA counties	(4) Non-MSA counties	(5) MSA counties	(6) MSA counties	(7) Income control	(8) Income control
Price change	1.270*	0.663	0.849	0.347	1.811**	1.415+	1.203*	0.692
× Short run	(0.531)	(0.552)	(1.026)	(0.843)	(0.581)	(0.737)	(0.510)	(0.543)
Price change	2.298**	1.982**	1.601	1.907+	2.997**	2.357**	2.210**	2.082**
× Medium run	(0.624)	(0.668)	(0.988)	(1.017)	(0.690)	(0.813)	(0.597)	(0.673)
Price change	3.285**	1.976**	0.502	2.091+	4.402**	1.981*	3.097**	2.156**
× Long run	(1.058)	(0.746)	(0.973)	(1.136)	(1.126)	(0.932)	(1.023)	(0.755)
Observations	37,908	37,908	27,014	27,014	10,894	10,894	37,232	37,232
Patient weights?	Yes	No	Yes	No	Yes	No	Yes	No

$**p < 0.01$, $*p < 0.05$, $+p < 0.1$. This table reports coefficients from ordinary least squares regressions in which log health care quantity supplied per Medicare patient is the dependent variable. These quantities, measured for each county and in each year 1993–2005, are regressed on the reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, as interacted with indicators for time after the consolidation. "Short Run" following the consolidation refers to 1997 and 1998, "Medium Run" refers to 1999 and 2000, while "Long Run" refers to 2001 through 2005. All specifications control for county fixed effects, state-by-year effects, and a set of year dummy variables interacted with the log of each county's 1990 population. Columns 1 and 2 also control for a set of year dummy variables interacted with an indicator for being in a metropolitan area; columns 7 and 8 control for county-by-year log personal income. Metropolitan area counties are defined using the Office of Management and Budget's 1999 definitions, with all counties in a Metropolitan Statistical Area or New England Consolidated Metropolitan Area considered to be metropolitan. Personal income data are from the Bureau of Economic Analysis. Additional controls and sources are as in Table 2.

Appendix Table E.11: **Summary Statistics for Patient Cohorts**

Patient Cohort:	Cardiovascular Disease		Myocardial Infarction		Back Pain	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Number of patients	1,372,791		264,716		880,236	
County characteristics						
Price change	0.00	(0.015)	0.00	(0.015)	0.00	(0.014)
Population (thousands)	816	(1,520)	801	(1,488)	782	(1,519)
Part B care in year following diagnosis						
Total quantity (RVUs)	56	(149)	134	(161)	69	(158)
Total charges	$1,948	($3,543)	$4,833	($5,318)	$2,465	($3,967)
Evaluation and Management visits	9	(11)	21	(19)	12	(13)
Any cardiac catheterization?	0.05		0.32			
Any cardiac stent?	0.013		0.12			
Any cardiac stress test?	0.11		0.24			
Any magnetic resonance image?					0.08	
Any physical therapy?					0.20	
Any steroid injection?					0.04	
Any spinal surgery?					0.02	
Hospital care in year following diagnosis						
Any hospitalization?	0.15		0.34		0.18	
Any hospitalization for condition?	0.11		0.12		0.03	
Hospitalizations	0.23	(0.69)	0.66	(1.24)	0.29	(0.79)
Hospitalizations for condition	0.16	(0.55)	0.16	(0.46)	0.03	(0.20)
Charges in all admissions	$4,367	($21,363)	$14,973	($43,458)	$5,221	($23,182)
Charges in admissions for condition	$3,129	($17,541)	$4,677	($22,269)	$505	($5,122)
Patient-level controls at time of diagnosis						
Age	67.2	(5.8)	70.8	(6.9)	68.4	(6.2)
Number of comorbidities	1.8	(1.5)	4.1	(2.6)	2.0	(2.0)

Source: Price change: *Federal Register*, various issues; county population: Census Bureau; Patient data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2.

Appendix Table E.12: **Effect of Reimbursement Rate on Patients with Fractures**

	(1) Hip-Fracture Treatment	(2) Office Visit Count	(3) Log Office Visit Count
Price change × Post-consolidation	0.0958 (0.225)	8.308 (6.361)	0.952** (0.331)
Sample Mean	0.630	20.77	2.650
Observations	96,308	96,308	96,308

**$p < 0.01$, *$p < 0.05$, +$p < 0.1$. This table reports coefficients from ordinary least squares regressions in which measures of the health care received by patients with hip fractures (cohorts defined in Appendix D.1) are the dependent variables. The sample is restricted to patients living in counties that satisfied our matching requirements, which are described in the text (the results are essentially unchanged when we run these regressions using an unrestricted sample of individuals with cardiovascular disease). These outcomes are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, in the county where the patient was first diagnosed, as interacted with an indicator for years after the consolidation. All specifications control for fixed effects by county of diagnosis, state-by-year effects, and indicators for the patient's age, being black, Hispanic, female, being eligible for Medicare due to end-stage renal disease, and being eligible for Medicare due to disability. The results are robust to controlling additionally for each patient's health as proxied for by a set of indicators for having the individual comorbidities defined by Elixhauser et al. (1998), as well as having 2, 3, 4, and 6 or more such comorbidities. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.13: **Effect of Reimbursement Rate on Treatment of Post-MI Patients**

	(1) Log Care	(2) Total Care	(3) Cath	(4) Stent	(5) Angioplasty	(6) Physician Visits	(7) Echo	(8) Stress Test
Price change × Post-Consolidation	1.101** (0.319)	82.79* (41.72)	0.655** (0.127)	0.182* (0.0753)	0.113 (0.0840)	12.32* (5.263)	0.211 (0.130)	0.0532 (0.156)
Sample Mean	4.377	134.1	0.320	0.0729	0.0601	21.46	0.490	0.242
Observations	225,851	226,388	226,388	226,388	226,388	221,238	226,388	226,388
Adjusted R^2	0.189	0.141	0.099	0.020	0.021	0.230	0.107	0.077

$**p < 0.01$, $*p < 0.05$, $+p < 0.1$. This table reports coefficients from ordinary least squares regressions in which the treatment received by patients after an acute myocardial infarction (MI) is the dependent variable. The dependent variable in columns 1 and 2 is total quantity of care, expressed in logs and levels, and in columns 3 through 8 is an indicator for receiving the relevant treatment in the year after diagnosis (excepting physician visits, reported in column 6, which are expressed as counts). These quantities, measured for each patient in the cohorts defined in Appendix D.1, are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, in the county where the patient was first diagnosed, interacted with an indicator for years after the consolidation. All specifications control for fixed effects by county of diagnosis, state-by-year effects, a set of year dummy variables interacted with the log of the county's 1990 population, indicators for the patient's age group (65–59, 70–74, 75–79, and 80–84), being black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and each comorbidity defined by Elixhauser et al. (1998), as well as having 2, 3, 4, and 6 or more such comorbidities. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.

Appendix Table E.14: **Effect of Reimbursement Rate on Hospitalizations Among Diabetics**

	(1) Hospitalization within 1 year of diagnosis	(2) Hospitalization within 2 years of diagnosis	(3) Hospitalization within 3 years of diagnosis	(4) Hospitalization within 4 years of diagnosis
Panel A: Hospitalizations for Stroke				
Price change × Post-consolidation	-0.0036 (0.0132)	0.014 (0.024)	0.020 (0.025)	-0.0024 (0.0358)
Sample Mean	0.008	0.014	0.020	0.025
Panel B: Hospitalizations for MI				
Price change × Post-consolidation	-0.008 (0.029)	-0.087 (0.047)	-0.079 (0.073)	-0.093 (0.085)
Sample Mean	0.021	0.038	0.052	0.064
Panel C: Hospitalizations for Renal Failure				
Price change × Post-consolidation	-0.020 (0.022)	-0.030 (0.033)	-0.015 (0.042)	-0.038 (0.049)
Sample Mean	0.017	0.029	0.040	0.050
Observations	624,469	624,469	624,469	624,469

$**p < 0.01$, $*p < 0.05$, $+p < 0.1$. This table reports coefficients from ordinary least squares regressions in which indicators for hospitalization within the specified length of time due to stroke (Panel A), myocardial infarction (Panel B), or renal failure (Panel C) for each Medicare patient in the diabetes cohort defined in Appendix D.1 is the dependent variable. These outcomes are regressed on reimbursement rate shocks resulting from the consolidation of Medicare's fee schedule areas in 1997, in the county where the patient was first diagnosed, as interacted with an indicator for years after the consolidation. All specifications control for fixed effects by county of diagnosis, state-by-year effects, and a set of year dummy variables interacted with the log of the county's 1990 population. They also control for indicators for the patient's age group (65–59, 70–74, 75–79, and 80–84), being black, Hispanic, female, eligible for Medicare due to end-stage renal disease, due to disability, enrolled in an HMO, and each comorbidity defined by Elixhauser et al. (1998), as well as having 2, 3, 4, and 6 or more such comorbidities. Sources: Price change: *Federal Register*, various issues; Medicare claims data: Medicare Research Identifiable Files, 5 percent sample, described in section 2.2; county population: Census Bureau.