Medicare and the Rise of American Medical Patenting: The Economics of User-Driven Innovation

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Abstract

Innovation is part inspiration and part perspiration. Inspiration often arises from the users of existing technologies, who may be best placed to see their shortcomings. History reveals that innovation in medical equipment and devices, on which our analysis focuses, closely fits this framework. We thus develop and estimate an equilibrium model which captures the idea-generation that results from physicians' interactions with patients; a feature we refer to as "innovating by doing." We explore such effects empirically by analyzing the 1965 introduction of the U.S. Medicare program, which substantially increased the flows of well-insured patients through physicians' practices. We find that increases in medical equipment and device patenting were largest in states that experienced relatively large expansions in insurance coverage due to the size of their elderly populations and the extent of the elderly's insurance coverage at baseline. Applying our model's structure, we estimate that the Medicare program led to a 20 to 30 percent increase in medical equipment and device patenting across the United States. We estimate that roughly half of this aggregate effect was due to the innovating by doing effect associated with patient encounters.

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1 Introduction

The decades following World War II came with substantial increases in health care spending, life expectancy, and medical innovation. The origins of this period's increases in life expectancy and health care spending are well documented (Newhouse, 1992; Chandra and Skinner, 2012; Cutler and McClellan, 2001; Cutler et al., 2006; Murphy and Topel, 2006). The rise in the pace of medical innovation, however, is less well understood. This is particularly true of innovation in medical equipment and devices.

As can be seen in Figure 1, the filing of patent applications associated with medical equipment and devices, expressed as a share of all patents, began a steady rise in the early 1960s. Further, medical patenting among U.S.-based inventors appears to break away from the medical patenting of inventors in other countries around 1969. The economics literature has surprisingly little to say about this secular rise in the development of medical equipment and devices. The bulk of the literature on the causes of medical innovation has focused on pharmaceuticals.

Our analysis of innovation in medical equipment proceeds in three steps. First, we discuss a rich set of case studies in the history of medical innovation to establish key differences between medical equipment and pharmaceuticals. Pharmaceuticals are, in large part, a product of laboratory science. By contrast, as the case studies help to establish, medical equipment and device innovations are often products of engineering insights that are developed by practitioners (Roberts, 1988). Innovation in medical equipment and devices can thus have a strong *innovating by doing* component. We present novel evidence that, in contrast to pharmaceutical patenting, medical equipment and device patenting is quite strongly positively correlated with variations in the size of the physician workforce across states. This relationship appears to hold across the full time period we study, which extends from the 1950s through the 1980s.

After developing these initial facts, we build a model with a central role for inno-

vating by doing effects. Our use of the phrase "innovating by doing" emphasizes the development of new commercial products by practitioners, based on the insights they obtain through the act of practicing itself. In the model, the development of new medical equipment requires both practical insights, derived from interactions between physicians and patients, and conscious effort to translate these insights into commercialized products. We describe the conditions under which strong correlations between the geography of practitioners and innovation will emerge. Further, the model motivates our empirical analysis of the introduction of Medicare, which increased the flows of comprehensively-insured patients into physicians' offices. Within the context of our model, it is precisely while treating patients with comprehensive coverage that physicians might gain insights into the shortcomings of cutting-edge treatments and medical technologies. Importantly for our purposes, Medicare's impact on coverage varied in predictable ways across geographic markets (Finkelstein, 2007). We use these variations to further explore our model's predictions.

This brings us to the core piece of our empirical analysis. In our analysis of Medicare's effects, we find that variations in Medicare's impact across states predict substantial variations in the rise of medical patenting. That is, in the states where Medicare generated its largest increases in insurance coverage, we observe larger increases in medical patenting than we would otherwise have predicted. While our primary estimates rely on patents filed by U.S. residents alone, we obtain similar estimates when we incorporate variations in patents filed within the United States by residents of other countries.

Interpreted through the lens of our model, our estimates imply that the Medicare program led to a 20 to 30 percent increase in medical equipment and device patenting across the United States. Across a range of plausible parameter values, we estimate that 25 to 75 percent of this aggregate effect is driven by the innovating by doing channel, and the rest by a market size channel. Importantly, these estimates of aggregate effects

use the model's structure to account for an important form of equilibrium feedback. We illustrate how the model's structure makes it possible to push beyond what one could have learned from reduced form evidence alone. Specifically, it allows us to draw inferences about the Medicare program's aggregate effect on innovation.

Our analysis contributes primarily to three literatures. Our most direct contribution is to the literature on the origins of medical innovation. As noted above, a substantial body of research has related pharmaceutical research and development activity to variations in potential profits. Papers of note have analyzed the response of pharmaceutical innovation to vaccine mandates (Finkelstein, 2004), to shifts in population demographics (Acemoglu and Linn, 2004), to the Orphan Drug Act (Yin, 2008), to global disease burdens (Dubois et al., 2015), to the introduction of Medicare Part D (Blume-Kohout and Sood, 2013), to drug formulary exclusions (Agha et al., 2020), and to variation in expected effective patent life (Budish et al., 2015). Surprisingly little research has focused on innovation related to medical equipment and devices.[1] A notable exception is Clemens and Rogers (2020), who analyze the effects of Civil War and World War I era demand on prosthetic device innovation. The literature's nearly exclusive focus on pharmaceutical innovation leaves a substantial gap, as pharmaceuticals account for a modest share of overall health sector spending and spending growth.[2] Further, as noted above,

[1]The current paper supplants an earlier analysis circulated as Clemens (2013). It is worth noting four key advances of the current analysis relative to this earlier, unpublished working paper. First, the earlier analysis relied exclusively on the NBER Patent Database (Hall et al., 2001), which significantly limited its ability to assess trends in medical innovation prior to Medicare's introduction. Second, the earlier paper did not include the current paper's analysis of cross-sectional relationships between medical patenting and the geography of the physician workforce. Third, the earlier analysis presented exclusively reduced form estimates of the effects of Medicare's implementation, while the current analysis connects our estimates more directly to our model of innovating by doing. Fourth, the earlier analysis relied on relatively broad technology "sub-categories," as defined in the NBER patent database, to identify innovation connected to medical equipment and devices. The earlier paper's use of sub-category 44 "nuclear and x-rays" swept in an overly broad set of patents other than diagnostic imaging patents associated with x-ray and nuclear imaging technologies. In the current analysis, we combine information from the USPTO's more detailed technology classes with information from the complementary International Patent Classification (IPC) system to construct more precisely defined counts of medical equipment and device patents.

[2]In historical data from the National Health Expenditure accounts, pharmaceuticals accounted for less

the forces that give rise to new medical equipment and devices can be economically distinct from those that give rise to new drugs. Understanding what forces shape the development of new medical equipment and devices is thus of independent interest.

Second, we contribute to the literature on endogenous technological progress. Formally, our analysis builds most closely on Acemoglu and Linn (2004) and Aghion and Howitt (1992). Our key extension relative to these models involves the phenomenon of innovation by practitioners. Conceptually, our paper relates to models of growth through learning by doing (Arrow, 1962; Greiner, 1996). In the models of Arrow and Greiner, productivity rises mechanically through experience. In our model, innovation hinges on an additional choice: for a physicians' insights to improve outcomes, they must be developed into commercialized products through costly effort. Akcigit et al. (2018) model a researcher's productivity as rising through both experience, which accrues exogenously, and through the intensity of their interactions with other researchers, which is a choice. In our model, insights arise through encounters between physicians and patients. Motivated by our context, we micro found the flow of idea-generating encounters as a function of the patient population's insurance coverage. This connects to our empirical analysis of the U.S. Medicare program's introduction.

Finally, we contribute to the literature on directed technical change, which captures the idea that innovation shifts in response to changes in its potential profitability (Acemoglu, 2002). Directed technical change has received attention in multiple literatures that connect endogenous growth theory with data. One literature of interest connects trends in demographics and educational attainment with shifts in the skill-

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than 10 percent of all health expenditures over the period under analysis. Indeed, from 1960 through 1980, pharmaceuticals as a share of all health spending declined from just under 10 percent to just under 5 percent. Over this same time period, combined spending on the categories "Total Durable Medical Equipment Expenditures" and "Other Non-Durable Medical Products Expenditures" are of the same magnitude as "Prescription Drug Expenditures." Importantly, medical technologies are key inputs to, and thus partial drivers of, the much broader expenditures associated with hospitals, physician and clinical services, and dental services.

complementarity of new technologies, which in turn affect wages (Acemoglu, 1998; Hémous and Olsen, Forthcomingb). Separately, an important environmental economics literature has identified effects of market incentives on a rich set of dimensions of innovation.[3] These include analyses of "clean" vs. "dirty" technologies (Acemoglu et al., 2012; Aghion et al., 2016; Popp, 2010), analyses of product attributes (Newell et al., 1999), and analyses of the effects of "induced" innovation on subsequent energy prices (Popp, 2002). We show that medical equipment and device patenting rose substantially in response to both the markets and innovation opportunities that came about due to the U.S. Medicare program.

This paper proceeds as follows. In section 2 we summarize prior research and present additional evidence on the role of practitioners in the development of medical equipment and devices. In section 3 we present our theoretical model. In section 4 we present our analysis of the cross-sectional relationship between medical innovation and the geography of the physician workforce. In section 5 we present our analysis of the effects of the introduction of Medicare on medical innovation. We conclude in section 6.

2 Where Does Medical Equipment and Device Innovation Come From?

This section presents an initial set of facts that motivate both our theoretical framework and the remainder of our empirical analysis. The facts come from a combination of industry case studies and patent data.

[3]Hémous and Olsen (Forthcominga) review much of the literature on directed technical change as it relates to both labor and environmental economics.

2.1 Case Studies in the Origins of Medical Innovation

A rich literature of industry case studies provides key insights into the nature of medical innovation during the time period of our analysis. Roberts (1988) writes:

> [My] personal experience, supported by the few relevant studies on innovation, indicates that... innovation in medical devices is usually based on engineering problem solving by individuals or small firms, is often incremental rather than radical, seldom depends on the results of long-term research in the basic sciences, and generally does not reflect the recent generation of fundamental new knowledge. It is a very different endeavor from drug innovation, indeed.

The case studies referenced by Roberts include detailed analyses of a sample of 34 medical-equipment innovations by Shaw (1985, 1986). In these analyses, Shaw finds that physicians were involved in the design of prototypes for 18 (just over half) of the 34 innovations. In an additional 11 cases, Shaw finds that the key insight was developed by a physician who subsequently approached a manufacturer. Physicians thus played a leading role in more than 80 percent of the innovations in Shaw's post-World War II sample. In complementary studies of scientific instruments, Von Hippel (1976) finds a conceptually similar pattern of "user-dominated innovation." Von Hippel (1976) found that practitioners, rather than manufacturers, were primarily responsible for roughly 80 percent of major innovations in scientific areas including Gas Chromatography, Nuclear Magnetic Resonance Spectrometry, Ultraviolet Spectrophotometry, and Transmission Electron Microscopes.

The insights of Shaw (1985, 1986), Von Hippel (1976), and Roberts (1988) apply to some of the most important medical innovations from the second half of the 20th century. In appendix B, we discuss two notable historical examples in some detail. We first

discuss Thomas Fogarty's development of the embolectomy catheter for removing blood clots, which is widely regard as the first device invented for the purpose of minimally invasive surgery. Practitioners also played central roles in the development of positive pressure ventilation equipment and techniques, which were important in reducing death rates among patients with polio.

Practitioners have also played leading roles in the development of technologies one might initially expect to result primarily from basic research or laboratory science. Physician Raymond Damadian, for example, developed the use of magnetic resonance imaging (MRI) for the purpose of cancer detection (Damadian, 1971, 1974). Similarly, physician Julio Palmaz, in partnership with Richard Schatz and Stewart Reuter, pioneered the development of coronary stents (Palmaz, 1988). Practitioners have also been heavily involved in the developments of more recent technologies including proton beam therapy (Slater et al., 1992) and robot-assisted surgery.

2.2 Data on the Geography of Patents and the Physician Workforce

In this section we describe our sources of data on patents as well as on the geography of the physician workforce. Our analysis makes use of patent data from two sources. One is the NBER patent database (Hall et al., 2001). The second is the "Comprehensive Universe of U.S. Patents (CUSP)" database assembled by Berkes (2018). These sources are complimentary in that the Berkes (2018) data have greater historical scope, which our analysis requires, while the NBER database is more complete with respect to its coding of geography and technology classes. In Appendix C.1, we more fully describe the manner in which we merge these databases to capitalize on their relative strengths.

We use two patent classification systems to identify medical equipment and device patents. Specifically, we use complementary information from the USPTO and IPC technology classification systems. Our classification of patents as medical equipment and

device patents is described in detail in appendix C.5.

Our analysis also makes use of a number of variables that describe the geographic distributions of physicians and other health care resources during the 1950s, 1960s, 1970s, and 1980s. These data come from the "Bureau of Health Professions Area Resource File, 1940-1990" (Health Resources and Services Administration. Bureau of Health Professions, 1994). We subsequently refer to this data set as the Historical Area Resource File. Appendix C.2 provides further detail on the manner in which we extract and shape these variables.

A key detail regarding the Historical Area Resource File is that it provides information on the geography of the physician workforce for select years, rather than all years, across the decades that are of interest for our analysis. Specifically, it provides detailed information on the geography of the physician workforce in 1968, 1975, and 1985. In general, we associate the 1968 physician workforce data with patent data from 1950 to 1969; we associate the 1975 physician workforce data with patent data from 1970 to 1979; and we associate the 1985 physician workforce data with patent data from 1980 to 1989. This coding of time periods works nicely for both our cross-sectional and panel analyses. When we turn to panel analyses, our interest is in the effects of the Medicare program's introduction. Introduced in 1965, the Medicare program's earliest possible influence on patenting activity would fall in the late 1960s.

Our analysis of the origins of Medicare requires us to generate variables that describe variations in the Medicare program's impact across states. Our approach extends measures of baseline elderly insurance coverage used by Finkelstein (2007). We augment the Finkelstein (2007) measures by accounting for variations in the size of the elderly population across states. In some specifications, we make additional use of cross-state variations in the Medicare program's early levels of expenditure per beneficiary. Appendices C.3 and C.4 provide a more detailed discussion of each of these variables.

2.3 Initial Facts on the Geography of Medical Innovation

The geography of post-World War II patenting for medical equipment and devices is consistent with the idea of user-dominated innovation. Figure 2 illustrates the cross-sectional, state-level relationship between medical patenting and the physician workforce using data from the sources described above. As noted above, we match patent data from 1950-1969, from 1970-1979, and from 1980-1989 with counts of physicians from 1968, 1975, and 1985 respectively.

Figure 2 shows that counts of physicians per capita were quite strongly correlated with medical equipment patenting during each of the time periods we consider. Panel A presents data from the 1950s and 1960s, Panel B presents data from the 1970s, and Panel C presents data from the 1980s. Both the patent data and the physician data are residualized with respect to counts of all non-medical (i.e., excluding both medical equipment and pharmaceutical patents) patents per capita, so that the correlations are unlikely to be driven exclusively by a tendency for physicians to locate in states with high levels of scientific output. As the figures reveal, the positive partial correlation between medical patenting and counts of physicians per capita is quite strong.

Panels D, E, and F of Figure 2 present equivalently constructed plots of the geography of the physician workforce and patenting related to pharmaceuticals. A comparison of panels D, E, and F to panels A, B, and C reveals that while patents for medical equipment and devices are positively correlated with the geography of the physician workforce, patents for pharmaceuticals are not. This provides evidence that the relationship we observe for medical equipment and device patenting does not merely reflect a tendency for areas with large numbers of physicians to be centers of medical research.

An additional fact of interest is that, throughout the time period we study, pharmaceutical patents were far more likely to be assigned to corporations than were medical equipment and device patents. Indeed, across the decades we analyze, roughly 85 per-

cent of pharmacuetical patents are coded by Hall et al. (2001) as having a corporate or university assignee. This is true of 60 percent of medical equipment and device patents. From the 1960s to the 1980s, the share of medical equipment and device patents that are likely assigned to corporations rose from 57 percent to 67 percent. These numbers bound the corporate sector's likely role, as Shaw (1985, 1986) finds that the ideas behind corporate patents for medical equipment often originate from practicing physicians.

3 Theory

In this section we build a model in which medical technology is developed through physician-driven innovating by doing. That is, our model emphasizes the idea that novel medical technologies arise from the insights physicians obtain while treating patients. The key idea is that insights regarding the weaknesses of existing technologies will tend to arise while one works with those technologies. In the context of medical devices, we highlight the idea that this experiential learning will tend to occur when physicians treat patients using technologies that are at or near the current frontier.

The specific model we develop is a continuous time model in which physicians obtain ideas during encounters with patients. A physician's likelihood of developing a successful commercial product depends on both the number of idea-generating encounters and the effort the physician devotes to commercialization. In the model, the flow of innovation is thus increasing in both the scale of the market, which is "global," and in the flow of comprehensively-insured patients, which is "local." Additionally, the model captures an equilibrium feedback mechanism, whereby an increase in the rate of innovation elsewhere reduces the expected returns to a given inventor's effort. The implications of these forces, once introduced, are reasonably intuitive. To ease the derivation of a fully characterized equilibrium, we make use of functional form assumptions.

The fully-specified model we present below captures the aspects of medical innovation we analyze empirically. We stress that a broader class of models would generate similar predictions. The crucial elements are the role of practicing physicians, the role of patients, and the role of the aggregate size of the market.[4]

3.1 The size of the market

Since the focus of our analysis is on the supply of innovation, we simplify our characterization of demand. Total spending on a class of medical products (our focus being on medical equipment and devices) is given by the number of patients, N, times average spending per patient, R.[5] We adopt the approach of Acemoglu and Linn (2004) and suppose that the market-leading manufacturer captures a share $0 < \gamma < 1$ of total spending on a given product as profits.[6] This gives a profit flow of $\pi = \gamma RN$.

The leading producer faces an endogenous probability ν of being replaced by a new producer. Let total spending, RN, grow at some rate g and the relevant discount factor be r. Let $r \approx g$ such that the expected discounted profit from a new innovation is:

$$\int_0^\infty e^{-(r+\nu)t} e^{gt} \pi(t) dt = \frac{\gamma RN}{\nu + r - g} \approx \frac{\gamma RN}{\nu}. \tag{1}$$

The key assumption for our results is that $\nu + r - g > 0$, such that discounted profits are finite. We assume $g - r \approx 0$ in what follows for the sake of analytical convenience. The exact formulation is not central to the analysis; what is crucial is that the expected

[4]A growing literature on the dissemination of knowledge has many of the same technical features as our model (Eaton and Kortum, 2001, 2002; Buera and Oberfield, 2020). In these models, less productive countries or agents learn from encounters with more productive counterparts and new techniques gradually spread to the whole economy. In our model, physicians do not learn from more productive individuals but from the encounters with patients. Physicians must then develop their insights into commercial products in order for their innovations to penetrate markets and generate income for the innovator.

[5]In our analysis of Medicare's introduction, we incorporate heterogeneity in health needs, and hence spending, across patient groups. To keep the notation streamlined, the model abstracts from this nuance.

[6]This can be micro-founded using a representative-agent framework, as in Acemoglu and Linn (2004).

profit from an innovation is increasing in the size of the market, γRN, and decreasing in the rate of innovation by potential competitors, ν.

3.2 Innovation by physicians

Potential innovators are practicing physicians who receive and develop ideas through innovating by doing. Specifically, each encounter with a patient produces an idea. An idea, i, has stochastic potential, $X \in (0, \infty)$ and can be developed and commercialized through effort as described below.

The potential of an idea is distributed according to the Fréchet distribution:

$$F(\chi) = P(X_i < \chi) = e^{-\chi^{-\theta}}, \tag{2}$$

where we impose $\theta > 1$. θ is inversely related to the variance of the potential of ideas. We assume that a physician can attempt to develop only a single idea at a time, and will thus choose to work on her most promising idea. That is, if the physician sees T patients, she will work on the idea with the highest $X = max\{X_1, X_2, ...X_T\}$. The Fréchet distribution has the convenient property that the maximum of T Fréchet distributions is also Fréchet. Specifically, the best idea received from T independent draws from patients is distributed according to:[7]

$$\tilde{F}^T(\chi) = P(X < \chi) = (F(\chi))^T = e^{-T\chi^{-\theta}}. \tag{3}$$

[7]The Fréchet distribution (also called a Type 2 Extreme value distribution) is frequently employed in the literature on international trade and growth (see Kortum (1997) and Eaton and Kortum (2002) and references therein). It arises naturally as an equilibrium object in models where countries adopt the best available technology or import from the cheapest potential supplier (Eaton and Kortum, 1999). This is so because for a large class of distributions including the Fréchet, the maximum of a series of draws converges to a Fréchet distribution. Consequently, while it is convenient to employ the Fréchet our results would have been approximately identical for a larger set of distributions, in particular all with tails fatter than the exponential.

Equation (3) first-order stochastically dominates the distribution in (2) for $T \geq 2$. That is, the more patients a physician encounters, the better will be the potential of the physicians' best idea. Following Small (1987) and Eaton and Kortum (2002), we will permit some correlation between the ideas from different patients by replacing equation (3) with:

$$F^T(\chi) = e^{-T^{1-\rho}\chi^{-\theta}}.$$

Here, $\rho = 0$ implies no correlation between ideas, while $\rho = 1$ implies perfect correlation, that is additional ideas have no new information and therefore no additional value.

The likelihood that a physician succeeds in developing an idea into a commercial product is given by the potential of the idea, X, and the effort the physician expends, W:

$$\tilde{z}(X, W) = \tilde{\delta} X W^{\frac{1}{\psi+1}}.$$

Here, $\psi > 0$, $\tilde{\delta} > 0$, and $\psi > 0$ implies decreasing returns to scale in effort. The parameter $\tilde{\delta}$ reflects state-level variations in the productivity with which ideas are developed.[8]

Under these assumptions, the expected rate at which new products are created is:

$$z \equiv E(\tilde{z}(X, W)) = \int_0^\infty \chi \tilde{\delta} W^{\frac{1}{\psi+1}} dF^T(\chi) = W^{\frac{1}{\psi+1}} \tilde{\delta} T^{\frac{1-\rho}{\theta}} \Gamma(1 - \frac{1}{\theta}),$$

where Γ is the gamma function and $\Gamma(1 - 1/\theta)$ is a constant from the perspective of the physician. Rearranging reveals that the cost of developing new products at rate z is:

[8]Note that this is isomorphic to a model in which the distribution of potential ideas varies with effort. We assume that the physician determines the effort she will spend on an idea before knowing the idea's potential. This is not entirely innocuous and is made for expositional convenience. Alternatively, a physician could make their choice of effort after seeing the potential of the best idea. Then W would depend on X. The qualitative results would remain identical but the math would be more complicated.

$$W(z) = \delta^{-(1+\psi)} T^{-\eta} \frac{1}{\psi+1} z^{\psi+1}. \tag{4}$$

In this expression, $\delta^{-(\psi+1)} \equiv (1+\psi)\Gamma(1-1/\theta)^{-(1+\psi)}\tilde{\delta}^{-(\psi+1)}$ is a productivity term, $\eta \equiv (1-\rho)(1+\psi)/\theta \geq 0$ captures innovating by doing effects, and ψ describes the production function's curvature. When $\psi \to 0$ the production function is linear and the returns to an individual physician's efforts are not diminishing. As $\psi \to \infty$, by contrast, idea generation is extremely convex, such that each physician effectively receives a fixed stock of ideas (of $\tilde{\delta}\Gamma(1-1/\theta)T^{(1-\rho)/\theta}$). The cost of developing ideas declines with the number of patients when $\eta > 0$. This effect is strongest when the ideas generated from each patient interaction are less correlated (ρ low), or when the variance of the signals is high (θ low). When $\eta = 0$, the development of higher quality products is purely a function of the effort exerted by the innovator, as in the classic model of Aghion and Howitt (1992). In the medical context, this may aptly describe the pharmaceutical sector.

Faced with the cost function of equation (4) and the profit function of equation (1), the physician chooses effort to solve the problem:

$$max_z \frac{\gamma RN}{\nu} z - \delta^{-(1+\psi)} T^{-\eta} \frac{1}{\psi+1} z^{\psi+1}, \tag{5}$$

such that innovation by physician j is given by

$$z_j = \delta^{\frac{1+\psi}{\psi}} \left[\frac{\gamma RN}{\nu} T_j^{\eta} \right]^{\frac{1}{\psi}}. \tag{6}$$

Recall that RN is the size of the market and T_j is physician j's number of idea-generating encounters with patients.

We assume a distinction between product markets and the more narrow market that determines each physician's patient flows. That is, we assume a nationally integrated product market and local markets for each physician's services. In particular, consider

innovation in a particular area s with M_s potential physician innovators. For simplicity, let each physician have the same number of well-insured patients, such that $T_s = N_s/M_s$ for all physicians in area s. Allow the efficiency of innovation, δ, to vary by area s and use equation (6) to write total innovation from an area as:

$$\nu_s = M_s z_s = M_s \delta_s^{\frac{1+\psi}{\psi}} (N_s/M_s)^{\eta/\psi} (\gamma R N)^{1/\psi} \nu^{-1/\psi}. \tag{7}$$

According to equation (7), local innovation depends positively on the number of local physicians, local productivity, the local number of patients per physician, and the profitability of the national market, and negatively on total innovation. We next define

$$\delta^{(1+\psi)/\psi} \equiv \left(\sum_s M_s \left[N_s/M_s \right]^{\eta/\psi} \delta_s^{(1+\psi)/\psi} \right) / \left(M \left[N/M \right]^{\eta/\psi} \right)$$

as the weighted, national average of productivity. We then solve for $\nu = \sum_s \nu_s$, substitute into equation (7), and divide by population, Pop_s, to obtain our expression for the expected per capita flow of innovation in region s:

$$\frac{\nu_s}{Pop_s} = \delta_s \frac{M_s}{Pop_s} (N_s/M_s)^{\eta/\psi} (\gamma R)^{\frac{1}{1+\psi}} (\delta_s/\delta)^{\psi} (N/M)^{\frac{(1-\eta/\psi)}{1+\psi}}. \tag{8}$$

Equation (8) makes clear that the innovation rate in a given area s, depends on both local and national terms. First, since innovation is done by practicing physicians, all else equal, the rate of innovation depends proportionately on the number of physicians per capita in area M_s/Pop_s and the productivity of local innovation, δ_s. Furthermore, due to innovating by doing effects innovation is positively helped by the number of patients per physician, N_s/M_s, though this effect is active only if such learning effects are positive, $\eta > 0$. Local innovation will also be affected by three national-level variables. It is positively related to total size market, γRN, negatively related to nationwide productivity, δ, and negatively related to the nationwide number of patients per physician. The

latter two relationships reflect an equilibrium effect. That is, they involve forces that reduce the returns to effort by increasing the likelihood that today's market leader will be displaced by future innovation.[9]

3.3 Transitioning to Empirics

We transition to our empirical analysis by taking logs of equation (8) and organizing terms to obtain:

$$ln(\frac{\nu_s}{Pop_s}) = ln(\frac{M_s}{Pop_s}) + \frac{\eta}{\psi} ln(\frac{N_s}{M_s}) + (1+\psi) ln(\delta_s) - \psi ln(\delta) + \frac{1}{1+\psi} ln(\gamma R) + \frac{(1-\frac{\eta}{\psi})}{1+\psi} ln(\frac{N}{M}). \tag{9}$$

The relationships in which we have greatest interest are the relationships between physicians, M_s, patient demand, N_s, and innovation. In the following sections, we present our approach to analyzing these relationships, and discuss the limitations to interpreting our results as well-identified estimates from our model.

It is pertinent for us to emphasize two observations regarding the variation with which we might identify model parameters. First, physician counts exhibit substantial variation across states, but exhibit relatively little variation over time in our data. Our analysis of the relationship between physician counts and medical innovation is thus cross-sectional. While this poses a hurdle to pinning down the causal role of physicians as drivers of medical innovation, there are nonetheless some intriguing fact patterns. Second, it is difficult if not impossible to measure and pin down exogenous cross-sectional variations in patient demand. We thus use the introduction of Medicare as a time and

[9]This also explains why innovation might depend negatively on the ratio $\frac{N}{M}$ holding local $\frac{N_s}{M_s}$ constant: more patients in the country has a positive impact on incentive to innovate through a market size effect, but a negative effect through the fact that other physicians innovate more. In principle either can dominate, though our later empirical analysis strongly supports that $\frac{\eta}{\psi} < 1$.

spatially varying shock to demand. This analysis builds on variation exploited by Finkelstein (2007), for which there is a strong causal argument.

4 Cross-Sectional Analysis of the Relationship between Patenting and Physician Counts

In this section we analyze the cross-sectional relationship between medical innovation and physician counts. We begin by discussing the connection between our theoretical model and the cross-sectional models we estimate. We then present and discuss the empirical relationships of interest.

4.1 Cross-Sectional Empirical Models

A first step is to consider the poisson regression model that follows naturally from the cross-sectional relationship described by equation (9). Defining $E[C_s|\cdot]$ to be the expected per capita count of medical patents, we can write:

$$E[C_s|\cdot] = exp(\alpha_N + \beta_1 log[M_s/Pop_s] + \beta_2 log[N_s/M_s] + \beta_2 log\delta_s), \tag{10}$$

Note that $\alpha_N = -\psi ln(\delta) + \frac{1}{1+\psi} ln(\gamma R) + \frac{(1-\eta/\psi)}{1+\psi} ln(N/M)$ is a national intercept in this cross-sectional analysis. As noted above, the primary relationship of interest in our cross-sectional analysis is the relationship between patenting per capita and M_s/Pop_s. We cannot cleanly identify β_1, however, because we lack clean cross-sectional measures of either patient demand per physician (N_s/M_s), or the local productivity parameter, δ_s. If either δ_s or N_s/M_s are correlated with both patenting and our measure of physicians per capita, we will not obtain an unbiased estimate. While we can investigate the sensitivity of our estimates of β_1 to the inclusion of controls that proxy for δ_s and N_s/M_s, this form

of robustness analysis is not perfect. We thus provide additional evidence in the form of two falsification checks, which are described below.

We begin by estimating regressions of the following form:

$$E[C_s|M_s/Pop_s, X_s] = exp(\alpha_N + \beta_1 log\,[M_s/Pop_s] + X_s\beta + \epsilon_s), \tag{11}$$

where X_s are various controls. The primary control variables we utilize include measures of non-medical patenting per capita, the number of natural scientists per capita, hospital spending per capita, and income per capita. We interpret non-medical patenting and scientists per capita as proxies for variations in an area's overall scientific productivity (δ_s). We interpret hospital spending and income per capita as proxies for overall patient demand (N_s).

In addition to simple robustness analyses, we conduct two placebo-style tests. First, we investigate whether counts of physicians per capita are correlated with pharmaceutical patenting. The key point of this analysis is that our model does not have predictions for the location of innovation driven by laboratory science. Our analysis of pharmaceutical patenting can thus shed light on whether the relationship between physicians and medical equipment patenting reflects a broader pattern in health-sector patenting. Second, we explore whether the correlation between counts of physicians and medical patenting are driven by practicing physicians or by research and teaching physicians. Our model emphasizes a principal role for practitioners.

4.2 Analysis of the Cross-Sectional Relationship between the Medical Innovation and the Physician Workforce

Table 2 presents estimates of equation (11). The results in panel A analyze the geography of medical patenting in the 1950s and 1960s, while the results in panel B involve

the 1970s and the results in panel C involve the 1980s. Results in columns 1 through 4 of each panel relate variables of interest to medical equipment and device patenting, while results in columns 5 through 8 relate these same variables to pharmaceutical patenting.[10]

The results in columns 1 through 4 reveal that there was a strong cross-sectional relationship between the geography of the physician workforce and the geography of medical equipment and device patenting during each of the time periods we analyze. The specification in column 1 corresponds quite closely with the graphical presentation of the data in Figure 2, as the regression controls solely for patenting in non-medical technology classes. In panel A, the coefficient on the log of the count of physicians per capita reveals that conditional on patenting rates in other technology categories, a 10 percent increase in the number of physicians per capita predicts a 7 percent increase in the rate of medical equipment patenting. Column 2 shows that this estimate is only modestly affected by including measures of the number of natural scientists per capita, income per capita, and hospital spending per capita as covariates. Finally, columns 3 and 4 reveal that these estimates are robust to whether the observations are weighted equally (columns 3 and 4) or according to each state's population (columns 1 and 2).

Our estimates for the 1970s and 1980s, which are reported in panels B and C, are similar in magnitude to the estimates in panel A. The estimates in column 1, for example, imply that a 10 percent difference in the number of physicians per capita predicts a 9 percent difference in medical equipment patenting in the 1970s and a 6 percent difference in the 1980s. The estimates associated with the 1980s are statistically weaker than those for the other time periods, though the estimates are of substantial economic magnitudes in each case. There was thus a sustained, though perhaps weakening, connection between

[10]The observation counts (49 observations in some columns and 48 observations in others) result from two facts. First, Hawaii and Alaska were not states until mid-way through the first time period in our analysis, and are thus excluded throughout. Second, the covariates we include in columns 2, 4, 6, and 8 were not available for the District of Columbia, which is thus dropped from these regressions.

the geography of the physician workforce and the geography of medical equipment and device patenting.

It is natural to ask whether the correlations found in columns 1 through 4 of Table 2 reflect a tendency for certain areas to be major centers of medical research. If so, these same areas would tend to have large flows of pharmaceutical patents. The estimates in columns 5 through 8 reveal that this is not the case. Columns 5 through 8 reveal that there was, if anything, a negative relationship between the geography of the physician workforce and the geography of pharmaceutical patenting across the time periods we analyze. As foreshadowed by panels D, E, and F of Figure 2, these estimates are noisier than the estimates associated with medical equipment and devices.[11] Looking across panels, estimates are larger in Panels A and B than in Panel C.

Together, the estimates from columns 5 through 8 suggest no systematic or enduring relationship between the geography of the physician workforce and the geography of pharmaceutical patenting. The positive estimates from columns 1 through 4 thus do not reflect patterns in health-sector patenting that extend outside of medical equipment and devices. The cross-sectional correlation between the physician workforce and medical patenting is thus exclusive to the categories of medical innovation for which our model predicts a relationship.

We next develop an additional set of facts of interest for distinguishing between laboratory science and practical science. To do so, we divide the physician workforce into practicing physicians, teaching physicians, and research physicians.[12] We present the results of this analysis in Table 3. In panels A and B, the predictive content of

[11]On average across all specifications in the table, standard errors for estimates of relationships with pharmaceutical innovation are roughly twice the size of standard errors for estimates of relationships with medical equipment and device patenting.

[12]In the Historical Area Resource File, this division of physicians is available in 1975 and 1985, but not for earlier years. Consequently, we use the 1975 physician counts in our analysis of patents from the 1950s and 1960s as well as from the 1970s.

variations in the geography of the physician workforce load entirely onto practicing physicians. The results for the 1980s (see panel C) are mixed. That is, in contrast with the estimates for the 1950s, 1960s, and 1970s, the estimates for the 1980s are sensitive to whether we weight observations equally or according to population. On the whole, however, the predictive power of practitioners relative to teaching and research MDs provides further support for the role of innovating by doing effects.

Comparing the 1980s with earlier periods, the relative weakness of the predictive power of the practitioner workforce is interesting in light of our earlier analysis. In Table 2, we showed that the overall relationship between the physician workforce and medical patenting was weaker for the 1980s than for the earlier decades. Together, we take these findings as suggestive that the role of practitioners may have weakened by the end of the time period we analyze. This could be driven by a variety of factors. For example, if the science underlying the technological frontier becomes more complex or interdisciplinary, then innovation may shift away from small-time inventors and towards larger firms. Similarly, the Food and Drug Administration's expanding role in the approval of medical devices would have increased the fixed costs of entry, which would similarly tend to increase the scale of the firms within which product development and commercialization occur. Both of these factors would thus tend to reduce the strength of the geographic relationship between the locations in which ideas are generated and the locations from which they are patented, which is what we have tracked in the data.

5 Analysis of the Effects of Medicare's Introduction on Medical Innovation

In this section we present our analysis of how the introduction of Medicare affected medical patenting. We begin with analyses that rely exclusively on variation in the

magnitude of Medicare's impact within the United States. We then present additional results that contrast patenting by U.S. residents with patenting by non-U.S. residents.

5.1 Empirical Framework for Analyzing Medicare's Impact

Our model specifies how the innovating by doing effect depends on the number of patients per physician, N_s/M_s. For our analysis of the effects of introducing Medicare, we allow for the fact that some patients may require a larger number of technologically intensive procedures than others, and therefore be more likely to spur innovation. Specifically, we replace the raw number of patients with an Innovation Opportunity Index that allows treatments for the elderly to be more numerous and/or intensive than treatments for the non-elderly. We define the Innovation Opportunity Index in state s as:

$$\Omega_s = \omega_s^O \mu_s^O Pop_s^O + \omega_s^Y \mu_s^Y Pop_s^Y. \tag{12}$$

In the above expression, Pop_s^O is the elderly population (those 65 and older), $\mu_s^O \in [0,1]$ is the fraction of the elderly that have full insurance (Medicare or otherwise), and $\omega_s^O > 0$ describes the amount of care required by insured elderly individuals relative to younger individuals. Variables with superscript "Y" refer to corresponding values for the young. The uninsured are assumed to receive treatments that are rudimentary, or less technologically advanced, and therefore less likely to spur new innovation.

Note that the key variable of interest in equation (10), as derived from our model, involves the number of innovation opportunities *per physician* ($\frac{N_s}{M_s}$). Data limitations inhibit us from conducting a per-physician analysis throughout, in particular when our samples incorporate observations from countries outside of the United States. Nonetheless, we are able to conduct a portion of our within-U.S. analysis using regression models that hew as closely to our theoretical model as possible. For these estimates, we replace $\frac{N_s}{M_s}$

in equation (10) with $\frac{\Omega_s}{M_s}$. Allowing for time variation and reordering terms gives us:

$$E[C_{s,t}|\cdot] = exp(\beta_1 log(\frac{M_{s,t}}{Pop_{s,t}}) + \beta_2 log(\frac{\Omega_{s,t}}{M_{s,t}}) + X_{s,t}\beta + \lambda_s + \lambda_t + \epsilon_{s,t}), \tag{13}$$

where λ_s and λ_t are state and time period fixed effects. In the panel specification described by equation (13), national trends in treatment intensity, coverage, and the elderly share of the population will be captured by time fixed effects. Note also that the inclusion of state fixed effects leaves very little variation in the number of physicians per capita, $M_{s,t}/Pop_{s,t}$, since the correlation of the state-level counts of physicians per capita exceeds 0.975 across the decades we analyze.

The Innovation Opportunity Index $\Omega_{s,t}$ is, of course, not directly observable. Our baseline approach to proxy for the index makes use of available information on its key inputs. We first normalize ω_s^Y to 1 for all time periods. Next, based on data from the National Health Expenditure accounts, we assume a value of 0.65 for μ_s^Y, which captures the pervasiveness of out-of-pocket spending (as a share of total spending) for non-elderly individuals.[13] Our results are only modestly sensitive to altering this assumption. Our estimates of $Pop_{s,t}^Y$ and $Pop_{s,t}^O$ rely on state level data on total population and Medicare enrollments. The parameter μ_s^O, which describes the pervasiveness of insurance coverage among the elderly (Elderly Coverage), captures variation generated by the Medicare program. Our value for the 1970s and 1980s reflects the universality of Medicare coverage, while our value for the 1950s and 1960s expands on variables from Finkelstein (2007), which capture the share of the elderly that were either uninsured or under-insured prior to Medicare's introduction. Finally, and again using data from the National Health Expenditure accounts, we apply two assumptions for the value of ω^O, which describes the intensity of care received by the elderly relative to the young. When our measure

[13]Using data from the National Health Expenditure Accounts, 0.65 is a rough estimate of the out-of-pocket spending share for non-elderly individuals in 1970.

of Elderly Coverage makes use of Finkelstein's measure of the fraction uninsured prior to Medicare, we assume $\omega^O = 2.5$. When we use Finkelstein's measure of the fraction under-insured, we assume $\omega^O = 2.0$.[14] As with other assumptions discussed above, our results are only modestly sensitive plausible variations in these assumptions. Taken together, we have:

$$\begin{aligned}\Omega_{s,t} &= \omega^O_{s,t}\mu^O_{s,t}Pop^O_{s,t} + \omega^Y_{s,t}\mu^Y_{s,t}Pop^Y_{s,t} \\ &= 2.5 \times \text{Elderly Coverage}_{s,t} \times Pop^O_{s,t} + 0.65 \times Pop^Y_{s,t}.\end{aligned}$$

Recall that prior to Medicare's introduction, Elderly Coverage$_{s,t}$ takes values reported by Finkelstein (2007), while after Medicare's introduction it is uniformly equal to 1.

After estimating equation (13), which is the empirical model most directly tied to our theoretical model, we pursue a broad set of robustness analyses. Our primary interest in this subsequent analysis is to establish that the empirical relationship between variations in medical patenting and variations in the Medicare program's expansion of insurance coverage is robust. To do this, we explore a range of alternative measures of the Medicare program's impact. Further, we incorporate a cross-country dimension to our analysis. To make this full set of analyses possible, we replace the $\frac{\Omega_{s,t}}{M_{s,t}}$ from equation (13) with $\frac{\Omega_{s,t}}{Pop_{s,t}}$. Here it is relevant to note that because $\frac{M_{s,t}}{Pop_{s,t}}$ is very strongly correlated over time, it matters little for our estimates of β_2 whether we divide $\Omega_{s,t}$ by population or by the number of physicians.[15]

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[14]In the earliest available data from the Medical Expenditure Panel Survey, which come from 1996, the ratio of the "mean events per person" for the elderly relative to younger adults is just under 2.5. The National Health Expenditure Accounts can also be used to construct rough estimates of the utilization of the elderly relative to the non-elderly. Reasonable approaches yield estimates in the range of 2 to 3 across the relevant years. When applying Finkelstein's measure of the fraction under-insured, our use of $\omega^O = 2.0$ applies a rough discount to account for the fact that some of the individuals in question started with non-comprehensive insurance rather than no insurance. Medicare would thus have constituted a smaller shift in coverage across this more broadly defined group.

[15]Note that when the number of physicians per capita, $M_{s,t}/Pop_{s,t}$, is included in the regression, our

In Appendix C.4, we discuss several alternative ways to characterize the effects of the Medicare program on the innovation opportunities associated with providing treatments to well-insured patients. We further demonstrate that our key results are robust to incorporating these alternative measures into our empirical analysis. The alternative measures take four general forms. First, we consider a set of alternative ways to construct the Innovation Opportunity Index. Second, we use our simpler measure, which is less guided by our model and more guided by the analysis of Finkelstein (2007). This second measure interacts our measures of the Uninsured Elderly (i.e., $1 - \text{Elderly Coverage}_{s,pre-1965}$) with time period dummy variables. Third, we extend the second approach by augmenting the change in the insured share of the population with cross-state variations in per beneficiary Medicare spending. Fourth, we construct a variable we call the Covered Market Share, which captures variations in the prevalence of insurance coverage across the entirety of a states' population. This variable has a greater conceptual similarity to the Innovation Opportunity Index than do the other variables, in that changes in its natural log can proxy for changes over time in the log of the number of idea-generating encounters.

5.2 Estimates Exploiting within-U.S. Variation in Medicare's Impact

This subsection proceeds in two parts. First, we present our baseline estimates of equation (13). Second, we combine these estimates with our equilibrium model to quantify the extent to which our innovating by doing effect and market size effect contributed to innovation in medical equipment and devices.

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estimate of β_2 will not be affected by dividing $\Omega_{s,t}$ by $Pop_{s,t}$ rather than by physicians, $M_{s,t}$. This can be seen in practice by comparing coefficients in columns 3 and 4 of Table 4 to those in columns 3 and 4 in panel A of Table 6. This choice does, however, have a mechanical impact on the estimate of β_1, which is the coefficient on $M_{s,t}/Pop_{s,t}$ itself. This can also be seen by comparing coefficients in columns 3 and 4 of Tables 4 and 6.

5.2.1 Baseline Empirical Estimates

We present our initial estimates of equation (13) in Table 4. The coefficients on the log of our measure of Innovation Opportunities Per Physician are economically substantial and statistically distinguishable from zero in all specifications. The estimates of η/ψ range between 0.58 and 0.84, which is consistent with an important role for innovating by doing effects, $\eta > 0$, as well as with our assumption that $\eta/\psi < 1$. The estimates are robust to the use of population weights as well as to the inclusion of controls for income per capita and other patenting activity within each state.

Estimates of the relationship between innovation and the number of physicians per capita are consistent with our earlier cross-sectional analysis. The estimates of interest range substantially across specifications, from 0.54 to 1.42. Consistent with this variability, the estimates have substantial standard errors and thus come with wide confidence intervals. This is not surprising, given the modest variations we observe in the number of physicians per capita over time. As noted previously, the correlation of the state-level physician counts exceeds 0.975 across the time periods in our sample.

5.2.2 Implications of Our Estimates for Medicare's Aggregate Effects

What do these estimates imply about the magnitude of Medicare's impact on medical equipment and device patenting? Below we show that answering this question requires considering three economic channels.[16] Two of these channels can be seen directly in equation (7), which we reproduce below:

$$\nu_s = M_s \delta_s^{\frac{1+\psi}{\psi}} \left(N_s/M_s\right)^{\eta/\psi} \left(\gamma R N\right)^{1/\psi} \nu^{-1/\psi}. \tag{14}$$

[16]Note that our analysis here assumes that the state-level counts of physicians (M_s) are held constant. Allowing for physician entry would add an additional channel of interest. We note that because the number of physicians is a stock, which will move slowly with changes in retirement behavior and expansions in available medical school slots, this fourth channel can be viewed as a "very long run" channel. The channels we emphasize can be viewed as short to medium run channels.

The above expression describes innovation in state s, ν_s, when overall innovation, ν, is held constant. The first channel that can be seen directly in the expression above captures the fact that Medicare resulted in a larger number of well-insured patients, N, on the integrated national product market for medical equipment. This reflects a classic *market size* effect that, as specified in our model, has an elasticity of $1/\psi$.[17] Second, Medicare generates an *innovating by doing* effect by increasing the localized flows of well-insured patients, N_s, which increases the rate at which physicians obtain insights that can advance the technical frontier. The introduction of this second force is our paper's novel addition to existing models of directed technical change. The innovation by doing elasticity is η/ψ.

In additional to these "partial" effects that occur when we hold ν constant, there is an equilibrium effect. This third channel captures the fact that an increase in innovation around the country reduces the gain from innovating by shortening the expected period of market dominance. We can see this by making use of the fact that $\nu \equiv \sum_s \nu_s$ to rearrange equation (7) and obtain:

$$\nu = \delta M^{\frac{\psi}{1+\psi}} (\gamma R N)^{\frac{1}{1+\psi}} (N/M)^{\frac{\eta}{1+\psi}}.$$

The above expression for overall innovation, v, features a market size elasticity given by $1/(1+\psi)$ and an innovating by doing elasticity given by $\eta/(1+\psi)$. We call these "total" to distinguish them from the partial elasticities described above. We can write them as:

$$\text{Total market size elasticity} = \frac{1}{1+\psi} = \frac{1/\psi}{1+1/\psi} = \frac{\text{partial market size}}{\text{partial market size+1}} < 1, \qquad (15)$$

[17] See Acemoglu (1998) as well as Dubois et al. (2015). Besides the size of the market, these papers also discuss a *price* effect from changes in the equilibrium prices at which the products are sold. Our assumption of a constant profit per patient, γR, ignores such effects.

$$\text{Total innovating by doing elasticity} = \frac{\eta/\psi}{1+1/\psi} = \frac{\text{partial innovating by doing}}{\text{partial market size+1}}. \quad (16)$$

The total elasticity of innovation with respect to an increase in the national number of patients is given by the sum of the "Total market size elasticity" and the "Total innovating by doing elasticity," or:

$$\text{Total elasticity} = \frac{1/\psi}{1+1/\psi} + \frac{\eta/\psi}{1+1/\psi} = \frac{1/\psi+\eta/\psi}{1+1/\psi}$$

Our estimates so far, as presented in Table 4 are of η/ψ. In what follows we take the average of the estimates in Table 4 and let $\eta/\psi \approx 0.7$. We use the expressions above to make progress in relating this estimate of η/ψ to Medicare's total effect.

Consider first the total market size elasticity. In the context of pharmaceuticals, Dubois et al. (2015) estimate a total market size elasticity of 0.25. In their review of the literature, they find that estimates are typically around 0.5, albeit with notable exceptions including Acemoglu and Linn (2004).[18] In a discussion of research on energy-related innovation, Popp (2010) observes that the most directly comparable estimate in the literature implies a long-run elasticity of 0.35. Drawing on these estimates, we consider the implications of market size elasticities ranging from 0.25 to 0.60. In Section 5.4 we provide complementary evidence for market size effects in this range by adding a

[18] Acemoglu and Linn (2004) find estimates around 4, which is inconsistent with our model. However, as they discuss their regressions are concerned with the "potential market size" as defined by demographics. When they compare this with "actual market size" their estimates are consistent with a total market-size elasticity of 1. Dubois et al. (2015) argue that an elasticity below 1 is natural because increased innovation by competitors reduces the value of the market. If ν in our model were to grow proportionately with N, then the total value of the market, $\gamma RN/\nu$ could not have grown, which contradictorily implies that there would not have been a market size effect. Consequently, the elasticity of ν with respect to N must be less than 1. The offsetting effect from the increased innovating by competitors goes through reduced market size and is itself proportional to the market size elasticity. As discussed in Acemoglu and Linn (2004), however, the result that the elasticity of ν with respect to N must be less than 1 is driven in part by the assumption of a Cobb-Douglas functional form for preferences.

cross-country dimension to our analysis.

Taken together, estimates of the "Total market size elasticity" and the "Partial innovating by doing elasticity" enable us to derive several quantities of interest. These include Medicare's overall impact on medical patenting, as well as the impact that is attributable to innovating by doing. Table 5 illustrates several steps in the underlying calculations under a range of alternative estimates for key parameters. Assume, for example, that the total market size elasticity is 0.25. This implies that $\psi = 3$ and, further, that the partial market size elasticity is $1/\psi = 1/3$. Connected with our estimate that $\eta/\psi \approx 0.7$, this further implies that $\eta = \psi \times 0.7 = 2.1$. Finally, we can substitute into equation (16) to estimate a "Total innovating by doing elasticity" of $.7/(1 + 1/3) = .525$. The "Total elasticity" is thus $0.25 + 0.525 = 0.775$. Note finally that 67.7 percent (0.525/0.775) of this total elasticity comes through the innovating by doing channel.

Given the estimates above, how large is the estimated effect of the Medicare program's introduction on medical patenting? Across the US states, the mean increase in the log of our measure of Innovation Opportunities Per Physician was 0.31. Multiplying this average change by an overall elasticity of 0.775, as derived above, yields our estimate that the Medicare program led to a $0.31 \times 0.775 = 24$ percent increase in medical equipment patenting. Of this, we estimate that 16.3 percentage points (estimated as 24×67.7 percent) is attributable to the innovating by doing effect.[19] The 24 percent increase in medical patenting accounts for just over one-fifth of the overall increase in medical patenting (relative to non-medical patenting) over the time period we study.[20]

[19]Note that these calculations ignore the second order effects arising from incorporating the state-specific changes to the innovation-opportunity index. In particular, by the definition of $\delta^{1+\psi}/\psi$, changes in the innovation-opportunity index might have an impact on the weighted productivity.

[20]In the overall patent counts, we observe that the average annual number of medical equipment patents filed by US inventors rose from 761 for 1950 to 1969 to 2206 for 1980 to 1989. This is an increase of 108 log points. The average annual number of non-medical patents filed by US inventors declined marginally, from 36796 for 1950 to 1969 to 35843 for 1980 to 1989. This is a decline or nearly 2 log points. Our estimate of the total impact of Medicare is thus equivalent to roughly 24/110, or 22 percent of the increase in the log of the number of medical equipment patents relative to the increase in the log of the number of

Absent the model's structure, reduced form evidence will tend to provide a misleading impression of the either the aggregate implications of innovating by doing or of the Medicare expansion's total effect. A "naive" reading of the empirical analysis would consider areas with little increase in the innovation opportunity index to be untreated by the expansion. The presence of ν in equation (7), however, makes clear that they are not. Neglecting the role of equilibrium effects would lead to an estimate of the contribution of the innovating by doing effect of $.7 \times .31 = 21.7$ percent. By failing to account for equilibrium effects, this naive calculation will tend to overstate the true aggregate implications of innovating by doing (a 16.3 percent increase in medical innovation, as calculated above). Similarly, because the naive calculation does not capture the market size effect, it will tend to understate Medicare's aggregate impact, which includes both the market size effect and the innovating by doing effect (a 24 percent increase in medical innovation, again as calculated above). The biases in the naive calculations both rise with the magnitude with the market size effect.

Both our estimate of Medicare's total effect and our estimate of the innovating by doing effect's contribution depend on the value we assume for the market size elasticity. Table 5 illustrates how these estimates shift if we assume an elasticity of 0.35, as reported by Popp (2010), or an elasticity of 0.6, which is slightly higher than several of the estimates from the literature on pharmaceutical innovation, as discussed by Dubois et al. (2015). A total market size elasticity of .6 implies $\psi = 0.67$ and $\eta = .48$. The total effect of Medicare would be a 27.3 percent increase in medical patenting, of which 8.7 percentage points come through the innovating by doing effect.

More generally, we can see in Table 5 that the estimated contribution of the innovating while doing effect declines as the estimate for the total market size elasticity rises. This can be seen analytically by considering the relative contributions of the $1/\psi$ and η/ψ

non-medical patents.

terms in equation (17). This reflects the fact that other innovators reduce the expected profits from capturing the market, and as such are the source of equilibrium feedback within the model.

5.3 Additional within-U.S. Estimates of Medicare's Impact

The analysis above raises a question of whether our estimates have truly distinguished between the market size elasticity and the partial innovating by doing elasticity. That is, how appropriate is our assumption that the markets for medical equipment and devices are primarily national or global rather than local?

A combination of external facts and supplemental analyses mitigate this potential concern. First, If the relevant product markets are sub-national, it would be natural to expect regional effects. In Appendix Table A.1, we thus report the results of analyses in which we add a regional version, meaning calculated across census regions, of our Innovation Opportunity Index to the analysis. In these regressions, the state-level Innovation Opportunity Index retains its magnitude and statistical significance, while the regional index exhibits no explanatory power. In related analysis, we find no evidence that effects differ when comparing large states with smaller states. Second, historical evidence reveals that product markets for medical equipment (specifically artificial arms and legs) have extended across state lines since at least as far back as the US Civil War (Clemens and Rogers, 2020; Hasegawa, 2012). During the middle of the 20th century, it is also clear that medical supply companies like Medtronic, Inc., were national in scope and were beginning to access markets in other countries (Medtronic, 2010). The assumption of a nationally integrated product market thus seems appropriate for our setting.

Table 6 presents the next wave of our analysis of the robustness of our estimates of the effects of the innovation opportunities created by the Medicare program. In panel A, the key variable of interest is the Innovation Opportunity Index, while in panel B it is the

Covered Market Share. As in Table 4, the coefficients on these variables are economically substantial and statistically distinguishable from zero in all specifications, with estimates ranging from 0.54 to 0.84.

Appendix Tables A.2 and A.3 show that the findings in Table 6 are not particularly sensitive to the manner in which we construct our measures of the Innovation Opportunity Index or the Covered Market Share. While columns 7 and 8 of Tables A.2 and A.3 replicate the results from columns 1 and 2 of Table 6, the initial 6 columns of both tables deploy alternative versions of these key variables of interest. For both variables one dimension along which the alternatives vary involves the two alternative variables used by Finkelstein (2007) to proxy for baseline coverage rates. While our preferred measure uses the Finkelstein measure of the fraction of elderly individuals who are underinsured, we present alternative estimates using her second measure, namely the fraction of individuals who lacked insurance altogether. For the Innovation Opportunity Index, a second dimension of difference involves our assumption about the evolution of coverage among the non-elderly. For the Covered Market Share, the second dimension of difference involves our assumption for "baseline" coverage. These dimensions of alternative measures of the Innovation Opportunity Index and of the Covered Market Share are described in greater detail in appendix C.4. The estimates in Tables A.2 and A.3 reveal that we obtain quite similar estimates regardless of the choices we make along these dimensions.

5.4 Cross-Country Evidence

In this section we add a cross-country dimension to our analysis. Recall from Figure 1 that, following the introduction of Medicare, medical equipment patenting rose substantially as a share of total patenting among US inventors, but quite modestly among foreign inventors filing patents in the United States. If the market for medical supplies

were a global, fully-integrated market, Figure 1 would suggest a limited role for the market size effect and a dominant role for the innovating by doing mechanism. That is, patenting among non-U.S. residents appears to have been little effected by Medicare's introduction. Alternatively, and perhaps more realistically, suppose that the market for medical equipment is only partly integrated between the US and the rest of the world. Under this assumption, the divergence shown in Figure 1 captures both a market size effect and an innovating by doing effect. In the empirical analysis that follows, we explore the extent to which this divergence loads onto the United States as a whole or onto the U.S. states in which Medicare generated disproportionately large expansions in insurance coverage.

For this analysis, we collapse patent counts to the time period-by-patent category-by-state or country level.[21] With respect to time periods, we refer to the 1970s as the Post Medicare Medium Run and to the 1980s as the Post Medicare Long Run. Our subscript for states (or countries) is s and our subscript for categories of technology is c. We estimate equations of the form:

$$\begin{aligned} E[C_{s,c,t}|\cdot\,] = exp(&\beta_M \text{US}_s \times \text{Medical Equipment}_c \times \text{Post Medicare Medium Run}_t \\ &+ \beta_L \text{US}_s \times \text{Medical Equipment}_c \times \text{Post Medicare Long Run}_t \\ &+ \beta_1 \ln(\text{Innovation Opportunity Index})_{c,s,t} + \lambda_{c,t} + \lambda_{p,s} + \lambda_{s,c}). \end{aligned} \tag{17}$$

Equation (17) takes a triple-difference structure. The policy variation of interest involves Medicare-driven variation in comprehensive coverage. This policy shock varies at the state (or country), by time period, by technology category level, as it affects the U.S. market for medical innovations. The specification thus includes state-by-period, period-

[21] By "patent category" we refer to "medical equipment" and "other" technology categories.

by-technology category, and state-by-technology category fixed effects.

The policy variation of interest is described in two ways. The first is by two variables that interact an indicator for observations from the United States with an indicator for medical equipment observations and two time period indicators.[22] The second is by the variable ln(Innovation Opportunity Index)$_{c,s,t}$ or, as a robustness check, the variable ln(Covered Market Share)$_{c,s,t}$. Note that the latter variables contain the cross-state variation utilized previously, while the former are binary variables that apply equally to all observations associated with medical equipment patenting in U.S. states in time periods after the introduction of Medicare. We present estimates of equation (17) as well as estimates that include one type of policy variable or the other, rather than including both simultaneously.

The cross-country data face multiple limitations. First, since the appearance of the broadest possible set of countries is not balanced over time, our estimates restrict the set of countries outside the United States to Japan, France, Germany, Canada, Switzerland, Italy, and the United Kingdom. Together, these countries account for the vast majority of patents for which the first inventor lives outside the United States during our sample period. An additional short-coming of the cross-country data is that we lack consistently defined, time-varying information on the number of physicians per capita. This is why we have excluded any physician covariates from this portion of our analysis. Our earlier analysis suggests that this exclusion will matter relatively little for the results.

The results are shown in Table 7. As in Table 6, the key variable of interest in panel A is the Innovation Opportunity Index, while in panel B it is the Covered Market Share. The estimates in columns 1 and 2 are quite similar to our earlier estimates. On average across the two specifications, the estimates imply that a 10 percent expansion in the

[22]These variables appear as US$_s$ $\times$ Medical Equipment$_c$ $\times$ Post Medicare Medium Run$_t$ and US$_s$ $\times$ Medical Equipment$_c$ $\times$ Post Medicare Long Run$_t$ in equation (17)

Innovation Opportunity Index or Covered Market Share generated a 7 percent increase in medical patenting rates (the partial effect). Additional results in Tables A.4 and A.5 reveal that these estimates are largely insensitive to the use of alternative assumptions in constructing either our Innovation Opportunity Index or our Covered Market Share variable.

In columns 3 and 4 of Table 7, we present estimates in which variation in Medicare's impact is described using simple indicator variables. Averaging once again across specifications, we estimate here that U.S. states saw relative increases in medical patenting on the order of 20 percent from the 1950s and 1960s to the 1970s, and on the order of 35 percent from the 1950s and 1960s to the 1980s. These estimates are moderately larger in magnitude than what one would predict by multiplying the estimates in columns 1 and 2 by the average change in our Covered Market Share variables.

In columns 5 and 6 we include all of the policy variables in the same specification. The estimates on the log of the innovation opportunity index and on the log of the covered market share are roughly 0.5 and 0.7 in the unweighted and weighted specifications respectively. The estimates thus continue to provide evidence for an important role for innovating while doing effects. Indeed, the point estimates differ negligibly from the estimates reported in Tables 4 and 6 we obtained when analyzing within-U.S. variations alone. The estimates thus remain within the range of parameter values for which we simulated Medicare's aggregate impacts in Table 5.

A final question of interest is whether the estimates in columns 3 through 6 of Table 7 can be used to make novel inferences regarding the magnitude of market size effects. The answer is no, due a mix of statistical and conceptual issues. The conceptual issue is that inferring an aggregate market size elasticity requires making two excessively strong assumptions. First, it would require assuming that the introduction of Medicare had no effect on innovation outside of the United States. Second, it would require

assuming away the possibility of learning effects that occur at the national level. The latter assumption could be violated, for example, by the knowledge transmission that occurs through professional associations, academic research, and other activities that are captured by the model of Akcigit et al. (2018). The statistical issue is that, due in part to feedback effects implied by the model, the implied market size elasticity is quite sensitive to small variations in our estimate of the U.S.-wide effect. To make robust inferences regarding the market size elasticity, our estimate of the U.S.-wide effect would need to be substantially more precise and less sensitive across specifications.

5.5 Additional Robustness Analyses

The Innovation Opportunity Index is constructed to translate into a key variable from our model as directly as possible. We present additional estimates using alternative measures, some of which relate closely to measures used in research on Medicare's aggregate impact on the hospital sector (Finkelstein, 2007). One variable makes direct use of the percentage point change in the fraction of individuals who lacked insurance. A second and third measure exploit cross-state variations in total Medicare spending per state resident. We then interact these changes with separate indicators for observations from either the 1970s or the 1980s. The estimates in Table A.7 reveal that each of these intuitively constructed policy variables predict increases in the rate of medical equipment patenting.

Finally, readers may worry that our grouping of observations into time periods masks differential trends in rates of medical equipment patenting across states or countries. To investigate this concern, we use annual data to produce event-study style estimates. Thus far, our time period groupings have been motivated by two factors. One is the selective availability of data on the physician workforce. The second is the fact that, during the 1950s and 1960s, medical patents are sparse when counted on an annual basis at the state

level. For annual estimates, we thus aggregate all U.S. states into a single geographic unit and all countries outside of the United States into a single geographic unit. We then estimate an equation that mirrors the version of equation (17) that relies on indicator variables rather than state-level estimates of the Covered Market Share.

The resulting estimates, as presented in Figure 3, are in line with what one would expect based on the time series presented in Figure 1. Reassuringly, the point estimates for years preceding Medicare's introduction provide no reason to worry that our estimates are driven by an upward pre-existing trend in U.S.-based medical equipment patenting. If anything, the pre-Medicare trend is in a modestly downward direction. Estimates for years in the 1950s and 1960s exhibit non-trivial variation from year to year, reflecting the relatively small number of patents from which these estimates are generated. Estimates are much smoother as we reach the 1970s and 1980s, and are consistent with estimates presented in Table 7. In the 1970s, rates of U.S.-based medical equipment patenting had risen by around 25 percent relative to patenting in other countries. By the 1980s, there were additional non-trivial increases.

6 Conclusion

The insights that arise from users of existing technologies are key inputs into innovation. In the health care context, a rich set of case studies reveal the importance of physician inventors, who have insights while treating their patients with existing technologies. A physician-inventor's incentive to develop these insights into commercial products then depends, at least in part, on the size of the market.

We capture these ideas by developing a model of endogenous technological progress with a central role for innovating by doing. Through the lens of our model, we then analyze the introduction of the U.S. Medicare program. Our empirical analysis shows that

Medicare's introduction significantly increased U.S.-based medical-equipment patenting. Increases in medical-equipment patenting were systematically larger in the U.S. states in which Medicare had greater impacts on insurance coverage.

Applying our model's structure, we estimate that Medicare's introduction increased aggregate medical equipment and device patenting by around 25 percent. We can further separate Medicare's overall effect into the roles of the traditional market size effect and the innovating by doing effect. We estimate that each of these channels are responsible for roughly half of the overall effect we observe. While the importance of the market size effect is well established in many settings, we show that innovating by doing effects may be equally relevant in driving an important class of technologies. While our analysis is limited to medical equipment, it illustrates that an exclusive focus on the incentives created by market size can miss important channels through which policy can shape the generation of ideas. The importance of innovating by doing in areas other than medical equipment remains an open question for future research.

A final point of interest involves the particulars on which inventors focus as they develop new technologies. A striking feature of medical innovation has been its tendency to expand the frontier of quality rather than reduce cost. The Medicare program initially paid both physicians and hospitals on a cost-plus basis, which may have encouraged innovation of precisely this form. That is, by expanding the prevalence of cost-plus payment, the U.S. Medicare program may have elevated medical innovation's emphasis on quality relative to cost. Whether such effects would enhance or reduce innovation's effects on welfare is a second open question for future research. The optimality, or efficiency, of the portfolio of innovations we realize depends on factors that extend beyond our study's scope.

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Figures and Tables

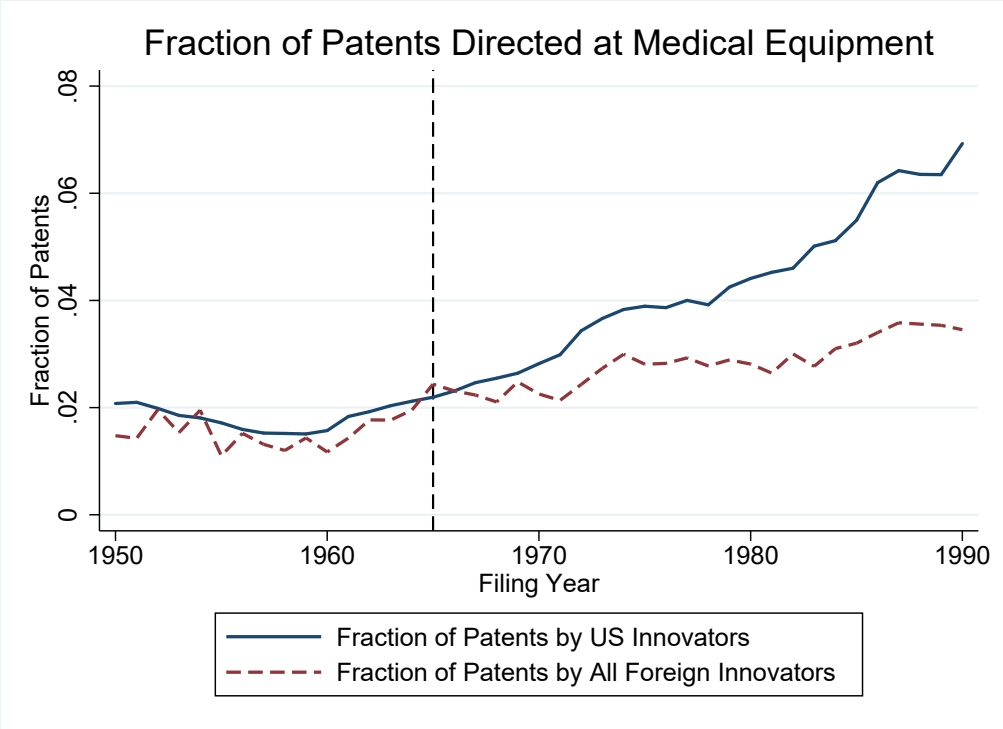
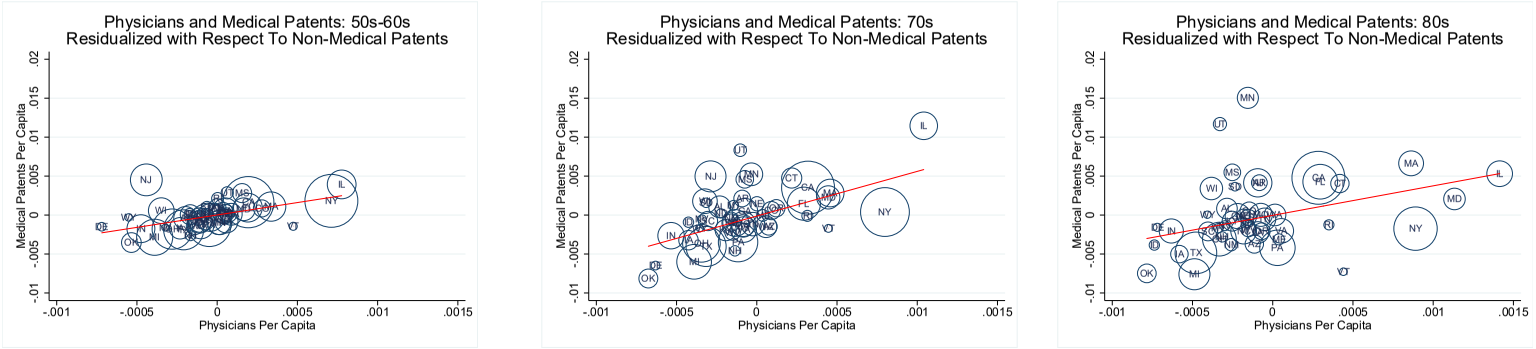


Figure 1: **Medical Patenting Over Time:** Some patent data.
Note: Series were constructed by the authors using data from the Comprehensive Universe of U.S. Patents database (Berkes, 2018) and the NBER Patent Database (Hall et al., 2001). As described in greater detail in appendix C.5, we classify patents as Medical Equipment based on a combination USPTO and IPC technology classification codes. First, we define the universe of medical patents to include all patents with IPC codes that begin with a61, which is titled "MEDICAL OR VETERINARY SCIENCE; HYGIENE," along with additional patents in USPTO codes 623 and 378, which correspond with "prostheses" and "x-ray and gamma ray systems," respectively. We then exclude the pharmaceutical patents associated with USPTO classes 424, 514, 435, and 800. These excluded classes involve Drugs (424 and 514), Chemistry (435), and Multi-Cellular Organisms. They aggregate to the full set of patents categorized in the NBER patent data base as "Drugs" or "Biotechnology." Patents are categorized as having a "US Innovator" if the first inventor's residence is listed as being as in the United States and as "Foreign" if the first inventor's residence is listed as being in a country other than the United States. If the first inventor's residence is not linked to a country, we exclude the patent. The year of each patent corresponds with the year in which it was filed.

Panel A: Medical Equipment (1950s-60s) *Panel B: Medical Equipment (1970s)* *Panel C: Medical Equipment (1980s)*



Panel D: Drug (1950s-60s) *Panel E: Drug (1970s)* *Panel F: Drug (1980s)*

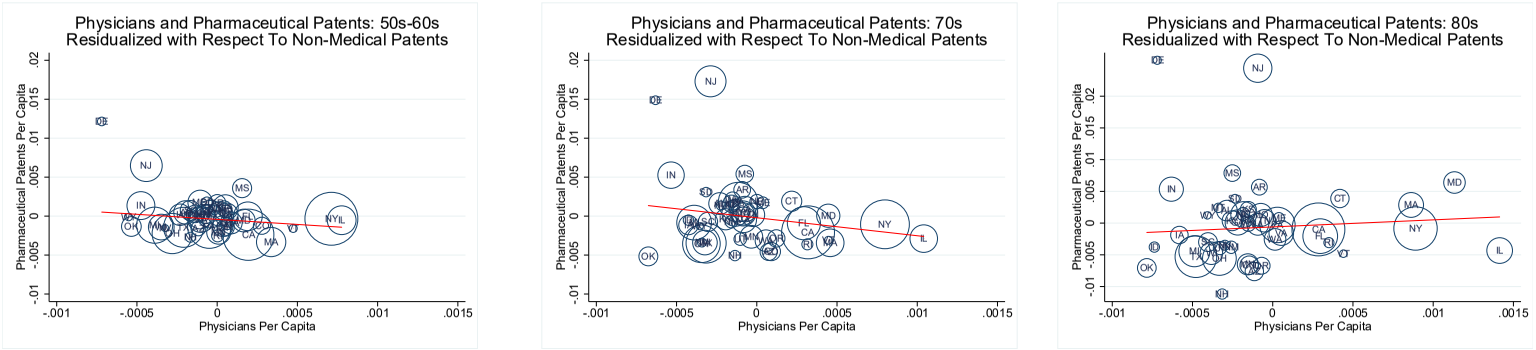


Figure 2: **Correlations between Physicians Per Capita and Medical Patenting Per Capita:**
Note: The figure presents partial correlations describing the relationship between counts of physicians per capita and counts of medical patents per capita. In each case, both the x-axis and y-axis variable have been residualized with respect to the number of non-medical patents per capita in each state. In panels A, B, and C, the y-axis variable corresponds with medical equipment and device patenting per capita. In panels D, E, and F, medical patents rest the y-axis variable corresponds with pharmaceutical patenting per capita. Panels A and D present data from the period extending from 1950 to 1969. Panels B and E present data from the period extending from 1970 to 1979. Panels C and F present data from the period extending from 1980 to 1989. The counts of physicians per capita come from the Historical Area Resource File. The measure used for Panels A and D corresponds with 1968, while the measure used for panels B and E corresponds with 1975, and the measure used for panels C and F corresponds with 1985. For ease of visual presentation, the figures exclude a single state for which the measure of residualized physicians per capita exceeded 0.03.

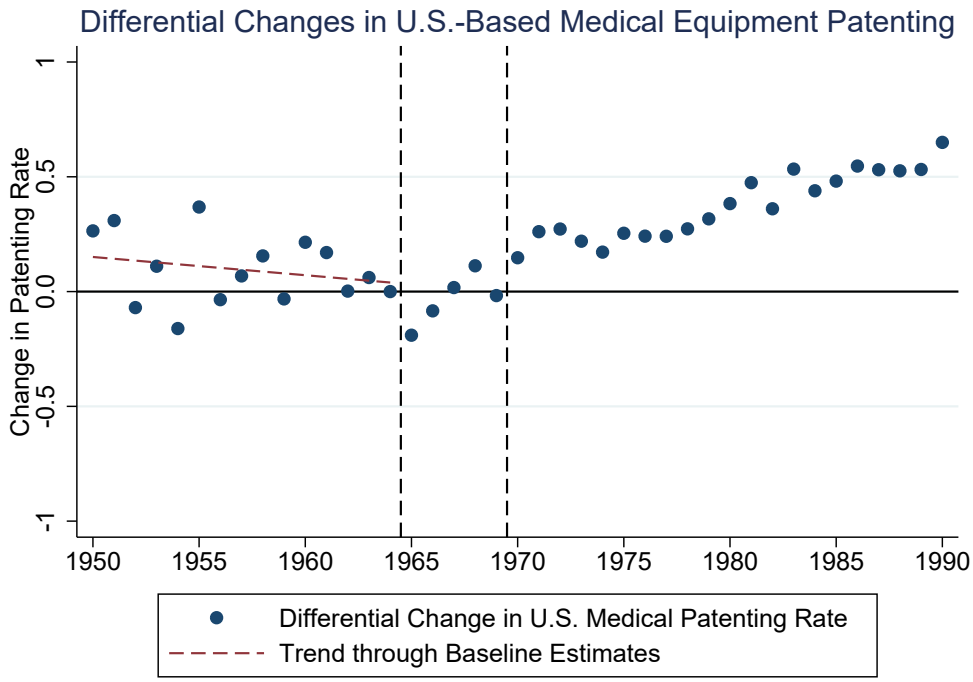


Figure 3: **Event-Study Estimates Using Annual Data:** Some patent data.
Note: The figures presents "event-study" estimates of differential changes in medical equipment patenting relative to other patenting among U.S. based inventors relative to inventors abroad. For this analysis, the data are collapsed at an annual level. Unlike previous analyses, which collapse at the level of individuals states or specific countries outside of the United States, for this analysis we collapse the U.S. data into a single geographic aggregate and the data for inventors outside the U.S. into a single geographic aggregate. We do this due to the sparcity of medical patents when counted on an annual basis at the state level during the 1950s and 1960s. The estimates are then of an equation that mirrors the version of equation (17) that lacks the Covered Market Share variable. It is thus a straightforward triple-difference style event study estimator. The construction of the medical equipment category is described in appendix C.5. Because this analysis is of the effects of the introduction of Medicare, the medical equipment aggregate excludes patents associated with drugs, veterinary medicine, dental care, and eye care.

Table 1: **Summary Statistics**

	(1)	(2)	(3)	(4)	(5)	(6)
	US-Based Inventors			Inventors Abroad		
	1950s-60s	1970s	1980s	1950s-60s	1970s	1980s
Annual Medical Patents Per Capita	0.371	0.616	0.862	0.0678	0.171	0.273
	(0.288)	(0.534)	(0.693)	(0.0889)	(0.133)	(0.201)
Annual Other Patents Per Capita	18.29	16.14	14.76	3.311	6.636	7.782
	(16.71)	(12.40)	(10.50)	(3.460)	(5.986)	(5.554)
Log Medical Patents Per Capita	-1.287	-0.806	-0.449	-3.211	-2.036	-1.525
	(0.802)	(0.814)	(0.794)	(1.041)	(0.851)	(0.763)
Log Other Patents Per Capita	2.589	2.544	2.484	0.800	1.603	1.812
	(0.798)	(0.691)	(0.648)	(0.967)	(0.830)	(0.783)
Innovation Opportunities Index	0.638	0.808	0.815	1	1	1
	(0.0250)	(0.0302)	(0.0439)	(0)	(0)	(0)
Covered Market Share	0.550	0.725	0.734	0.900	0.900	0.900
	(0)	(0.0447)	(0.0567)	(0)	(0)	(0)
Baseline Uninsured Per Cap.	0.0547	0.0547	0.0547	0	0	0
	(0.0121)	(0.0121)	(0.0121)	(0)	(0)	(0)
Baseline Underinsured Per Cap.	0.0873	0.0873	0.0873	0	0	0
	(0.0223)	(0.0223)	(0.0223)	(0)	(0)	(0)
MDs Per Cap.	0.00130	0.00158	0.00210	.	.	.
	(0.000530)	(0.000633)	(0.000805)	(.)	(.)	(.)
Teaching and Research MDs Per Cap.	.	0.0000523	0.000108	.	.	.
	(.)	(0.0000413)	(0.0000927)	(.)	(.)	(.)
Practicing MDs Per Cap.	.	0.00152	0.00200	.	.	.
	(.)	(0.000596)	(0.000722)	(.)	(.)	(.)
Income Per Capita	6372.4	10478.2	11812.9	.	.	.
	(1523.1)	(1740.2)	(2176.7)	(.)	(.)	(.)
Hospital Spending Per Cap.	.	144.4	103.6	.	.	.
	(.)	(84.14)	(71.60)	(.)	(.)	(.)
Scientists Per Cap.	0.00141	0.00119	.	.	.	.
	(0.00139)	(0.00128)	(.)	(.)	(.)	(.)
Observations	49	49	49	7	7	7

Note: The table presents summary statistics on the key variables underlying our analysis. Counts of patents come from the NBER patent database (Hall et al., 2001) and the "Comprehensive Universe of U.S. Patents (CUSP)" database assembled by Berkes (2018). Our measure of the "Baseline Uninsured Per Cap." comes from Finkelstein (2007). The Covered Market Share variables contain estimates of the fraction of medical spending that is financed by a third party rather than out of pocket. The construction of these variables is described in greater detail in appendix C. Information on the number of MDs per capita, Income per capita and hospital spending per capita come from the Historical Area Resource File. Information on the number of Scientists per capita comes from historical editions of the Statistical Abstract of the United States. Sourcing for all variables is described in greater detail in appendix C. The 7 observations associated with "Inventors Abroad" correspond with Japan, France, Germany, Canada, Switzerland, Italy, and the United Kingdom.

Table 2: **Analysis of the Geography of Post-World War II Medical Patenting**

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Medical Patenting				Pharmaceutical Patenting			
Panel A	Time Period: 1950-1970							
Log MDs Per Cap. (1968)	0.67**	0.68**	0.63**	0.73**	-0.68	-0.55	-0.78**	-1.00*
	(0.22)	(0.18)	(0.13)	(0.19)	(0.56)	(0.55)	(0.28)	(0.43)
Log Non-Medical Patents Per Cap.	0.73**	0.49**	0.66**	0.45**	1.57**	1.39**	1.59**	1.67**
	(0.13)	(0.09)	(0.08)	(0.09)	(0.25)	(0.23)	(0.08)	(0.19)
Panel B	Time Period: 1971-1980							
Log MDs Per Cap. (1975)	0.89**	0.78**	0.80**	1.05**	-0.85	-1.15*	-0.72+	-1.14**
	(0.24)	(0.24)	(0.21)	(0.23)	(0.56)	(0.48)	(0.38)	(0.41)
Log Non-Medical Patents Per Cap.	0.76**	0.54**	0.73**	0.53**	1.75**	1.37**	1.65**	1.46**
	(0.12)	(0.12)	(0.11)	(0.13)	(0.33)	(0.25)	(0.14)	(0.25)
Panel C	Time Period: 1981-1990							
Log MDs Per Cap. (1985)	0.66*	0.48	0.62**	0.53**	0.22	-0.31	0.35	-0.27
	(0.28)	(0.29)	(0.15)	(0.18)	(0.53)	(0.31)	(0.46)	(0.35)
Log Non-Medical Patents Per Cap.	0.80**	0.72**	0.83**	0.84**	1.36**	0.71**	1.36**	0.80**
	(0.14)	(0.19)	(0.07)	(0.20)	(0.37)	(0.15)	(0.21)	(0.21)
N	49	48	49	48	49	48	49	48
Weighted	Yes	Yes	No	No	Yes	Yes	No	No
Other Controls?	No	Yes	No	Yes	No	Yes	No	Yes

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of the cross-sectional relationship between medical equipment and device patents per capita and the geography of the physician workforce. Each entry in the table is an estimate of equation (11). In columns 1 through 4, the dependent variable is a state-level count of medical equipment and device patents per capita. In columns 5 through 8, the dependent variable is a state-level count of pharmaceutical patents per capita. In the specifications presented in columns 1, 3, 5, and 7, the only additional covariate in the model involves the number of non-medical patents per capita. The specifications in columns 2, 4, 6, and 8 add the number of natural scientists per state resident, hospital spending per capita, and income per capita. The specifications in columns 1, 2, 5, and 6 weight observations according to state population, while the observations in other columns are equally weighted. In panel A, observations are associated with 1950 through 1970. In panel B, observations are associated with 1971 through 1980. In panel C, observations are associated with 1981 through 1990.

Table 3: **Practicing vs. Research/Teaching MDs and Medical Patenting**

	(1)	(2)	(3)	(4)
Dependent Variable	Medical Patenting			
Panel A	Time Period: 1951-1970			
Log Practicing MDs Per Cap. (1975)	1.00**	1.07**	0.94**	1.13**
	(0.29)	(0.21)	(0.19)	(0.22)
Log Teaching and Research MDs Per Cap. (1975)	-0.12	-0.18	-0.12*	-0.14*
	(0.11)	(0.11)	(0.06)	(0.07)
Log Scientists Per Cap. (1964)		0.20		0.10
		(0.13)		(0.16)
Log Hosp. Spend. Per Cap. (1975)		0.01		-0.07
		(0.06)		(0.07)
Log Income Per Cap. (1959)		0.71**		0.48
		(0.25)		(0.30)
Log Non-Medical Patents Per Cap.	0.66**	0.45**	0.62**	0.42**
	(0.10)	(0.07)	(0.08)	(0.09)
Panel B	Time Period: 1971-1980			
Log Practicing MDs Per Cap. (1975)	0.99**	1.01**	0.63*	1.01**
	(0.29)	(0.30)	(0.28)	(0.25)
Log Teaching and Research MDs Per Cap. (1975)	-0.05	-0.14	0.10	0.03
	(0.12)	(0.14)	(0.10)	(0.07)
Log Scientists Per Cap. (1975)		0.17		0.06
		(0.20)		(0.19)
Log Hosp. Spend. Per Cap. (1975)		-0.05		-0.11
		(0.06)		(0.06)
Log Income Per Cap. (1975)		0.90+		0.13
		(0.51)		(0.66)
Log Non-Medical Patents Per Cap.	0.75**	0.50**	0.74**	0.52**
	(0.11)	(0.13)	(0.11)	(0.13)
Panel C	Time Period: 1981-1990			
Log Practicing MDs Per Cap. (1985)	0.78	0.71+	0.05	-0.04
	(0.51)	(0.41)	(0.40)	(0.46)
Log Teaching and Research MDs Per Cap. (1985)	-0.05	-0.12	0.29+	0.29
	(0.20)	(0.18)	(0.15)	(0.20)
Log Scientists Per Cap. (1975)		0.08		0.00
		(0.28)		(0.19)
Log Hosp. Spend. Per Cap. 1985)		-0.12		-0.12
		(0.11)		(0.15)
Log Income Per Cap. (1985), (1000s)		0.15		-0.51
		(0.54)		(0.66)
Log Non-Medical Patents Per Cap.	0.79**	0.68**	0.85**	0.88**
	(0.14)	(0.21)	(0.07)	(0.21)
N	49	48	49	48
Weighted	Yes	Yes	No	No

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels. The estimates in this table follow the same pattern as the estimates presented in columns 1 through 4 of Table 2. The key difference is that the measure of physicians per capita is replaced with separate measures of the number of practicing physicians per capita and the number of teaching and research physicians per capita.

Table 4: **Model Estimates Driven by Medicare's Introduction within the United States**

	(1)	(2)	(3)	(4)
Dependent Variable	Medical Patenting			
Log Innovation Opportunities Per Physician	0.62**	0.84**	0.58*	0.84**
	(0.22)	(0.19)	(0.29)	(0.21)
Log MDs Per Cap.	0.85*	1.42*	0.54	1.28+
	(0.39)	(0.61)	(0.46)	(0.71)
Log Income Per Cap.			0.81*	0.33
			(0.33)	(0.37)
N	147	147	147	147
Number of Clusters	49	49	49	49
Weighted	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70
Controls for Log Other Patents	Yes	Yes	Yes	Yes
Non-US Obs.	No	No	No	No

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (13). The 147 observations are associated with 49 states across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variables is described in detail in the main text and in appendix C.4. The key independent variable is the log of our measure of Innovation Opportunities per Practicing Physician. As indicated in the body of the table, the specifications in columns 1 and 3 equally weight all observations, while columns 2 and 4 are weighted according to each state's population during the first time period. All specifications control for state and time period fixed effects, as well as interactions between the log of non-medical patents per capita and a set of time period dummy variables. All specifications also include the log of the number of physicians per capita. Columns 3 and 4 additionally include the log of income per capita. Standard errors account for correlation clusters across time at the state level.

Table 5: **Implications of Model Estimates for the Overall Effects of Medicare**

		(1)	(2)	(3)
		Total Market Size Elasticity: $1/(1+1/\psi)$		
		0.25	0.35	0.6
Panel A: Implied Value of ψ				
Assumed Partial	0.5	3.000	1.867	0.667
Innovating by Doing	0.7	3.000	1.867	0.667
Elasticity: η/ψ	0.9	3.000	1.867	0.667
Panel B: Implied Value of η				
Assumed Partial	0.5	1.500	0.933	0.333
Innovating by Doing	0.7	2.100	1.300	0.477
Elasticity: η/ψ	0.9	2.700	1.667	0.600
Panel C: Implied Total Innovating by Doing Elasticity				
Assumed Partial	0.5	0.375	0.325	0.200
Innovating by Doing	0.7	0.525	0.455	0.280
Elasticity: η/ψ	0.9	0.675	0.585	0.360
Panel D: Percent Increase in Innovation Due to Medicare (From 0.31 rise in ln(Innovation Opportunity Index))				
Assumed Partial	0.5	0.194	0.209	0.248
Innovating by Doing	0.7	0.240	0.250	0.273
Elasticity: η/ψ	0.9	0.287	0.290	0.298
Panel E: Percent Increase in Innovation Due to Medicare through the Innovating by Doing Channel				
Assumed Partial	0.5	0.116	0.101	0.062
Innovating by Doing	0.7	0.163	0.141	0.087
Elasticity: η/ψ	0.9	0.209	0.181	0.112

Note: This table illustrates how our model parameters and empirical facts connect to generate estimates of Medicare's impact on innovation. The columns illustrate how the estimated effects evolve under alternative assumptions for the market size elasticity. Within each panel, the three rows of estimates illustrate how the estimated effects evolve under alternative assumptions for the partial innovating while doing effect. Note that the estimates in panel D are obtained by multiplying the sum of the total market size elasticity and the total innovating by doing elasticity by 0.31, which was the average increase in the log of our innovation opportunity index (the key variable used to estimate the partial innovating while doing elasticity) across states. Recall that the total market size elasticity varies across columns, while the total innovating by doing elasticities, which vary with both the market size elasticity and the partial innovating by doing elasticity, are reported in panel C. The formula for the total innovating by doing elasticity, $\frac{\eta/\psi}{1+1/\psi}$, comes from equation (16). Finally, the effects of Medicare through the innovating by doing channel, as reported in panel E, are calculated as 0.31 multiplied by the total innovating by doing elasticity.

Table 6: **Effects of Medicare's Introduction: Within-U.S. Analysis**

	(1)	(2)	(3)	(4)
Dependent Variable	Medical Patenting			
Panel A:				
Log Innovation Opportunity Index	0.58**	0.69**	0.58*	0.84**
	(0.20)	(0.16)	(0.29)	(0.21)
Log MDs Per Cap.			-0.04	0.44
			(0.34)	(0.59)
Log Income Per Cap.			0.81*	0.33
			(0.33)	(0.37)
Panel B:				
Log Covered Market Share	0.55**	0.63**	0.54+	0.76**
	(0.19)	(0.14)	(0.28)	(0.21)
Log MDs Per Cap.			-0.04	0.43
			(0.34)	(0.58)
Log Income Per Cap.			0.81*	0.32
			(0.33)	(0.37)
N	147	147	147	147
Number of Clusters	49	49	49	49
Weighted	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70
Controls for Log Other Patents	Yes	Yes	Yes	Yes
Non-US Obs.	No	No	No	No

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (13). The 147 observations are associated with 49 states across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variables is described in detail in the main text and in appendix C.4. In panel A, the key independent variable is the log of the Innovation Opportunity Index, which is a proxy for the volume of technologically intensive procedures that are delivered. In panel B the key independent variable is the log of the Covered Market Share, which is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1 and 3 equally weight all observations, while columns 2 and 4 are weighted according to each state's population during the first time period. All specifications control for state and time period fixed effects, as well as interactions between the log of non-medical patents per capita and a set of time period dummy variables. Columns 3 and 4 additionally include the log of the number of doctors per capita and income per capita. Standard errors account for correlation clusters across time at the state level.

Table 7: **Effects of Medicare's Introduction: Cross-Country Analysis**

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Medical Patenting					
Panel A						
Log Innovation Opportunity Index	0.66*	0.78**			0.52+	0.70**
	(0.30)	(0.30)			(0.30)	(0.26)
1970s x Med. Equip. x US State			0.35+	0.09	0.23	-0.07
			(0.19)	(0.13)	(0.20)	(0.14)
1980s x Med. Equip. x US State			0.42**	0.28*	0.30*	0.11
			(0.12)	(0.11)	(0.13)	(0.12)
Panel B						
Log Covered Market Share	0.62*	0.70**			0.49+	0.65**
	(0.28)	(0.26)			(0.29)	(0.22)
1970s x Med. Equip. x US State			0.35+	0.09	0.22	-0.09
			(0.19)	(0.13)	(0.20)	(0.14)
1980s x Med. Equip. x US State			0.42**	0.28*	0.29*	0.10
			(0.12)	(0.11)	(0.13)	(0.13)
N	336	336	336	336	336	336
Number of Clusters	56	56	56	56	56	56
Weighted	No	Base Pop.	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (17). The 336 observations are associated with 49 states and 7 large foreign countries across 2 categories of innovation and across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variables is described in detail in the main text and in appendix C.4. In panel A, the key independent variable is the log of the Innovation Opportunity Index, which is a proxy for the volume of technologically intensive procedures that are delivered. In panel B the key independent variable is the log of the Covered Market Share, which is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1 and 3 equally weight all observations, while columns 2 and 4 are weighted according to each state's population during the first time period. All specifications control for time period-by-technology category fixed effects, state-by-technology category fixed effects, and state-by-time period fixed effects. Standard errors account for correlation clusters across time at the state level.

Appendix Material

A Supplemental Figures and Tables

Appendix Table A.1: Model Estimates Driven by Medicare's Introduction within the United States: Robustness to the Inclusion of a Regional Innovation Opportunity Index

	(1)	(2)	(3)	(4)
Dependent Variable	Medical Patenting			
Log Innovation Opportunities Per Physician	0.69**	0.79**	0.62*	0.79**
	(0.18)	(0.17)	(0.28)	(0.22)
Log Innovation Opp's Per Physician across Census Division	-0.37	0.60	-0.23	0.77
	(0.72)	(0.81)	(0.65)	(0.82)
Log MDs Per Cap.	0.80+	1.58*	0.52	1.45*
	(0.42)	(0.65)	(0.47)	(0.72)
Log Income Per Cap.			0.80*	0.40
			(0.34)	(0.32)
N	147	147	147	147
Number of Clusters	49	49	49	49
Weighted	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70
Controls for Log Other Patents	Yes	Yes	Yes	Yes
Non-US Obs.	No	No	No	No

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (13). The 147 observations are associated with 49 states across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variables is described in detail in the main text and in appendix C.4. The key independent variable is the log of our measure of Innovation Opportunities per Practicing Physician. As indicated in the body of the table, the specifications in columns 1 and 3 equally weight all observations, while columns 2 and 4 are weighted according to each state's population during the first time period. All specifications control for state and time period fixed effects, as well as interactions between the log of non-medical patents per capita and a set of time period dummy variables. All specifications also include the log of the number of physicians per capita. Columns 3 and 4 additionally include the log of income per capita. Standard errors account for correlation clusters across time at the state level.

Appendix Table A.2: Effects of Medicare's Introduction: Robustness of within-U.S. Estimates to Alternative Definitions of the Innovation Opportunity Index

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Medical Patenting							
Log Innovation Opportunity Index V2	0.55**	0.59**						
	(0.18)	(0.15)						
Log Innovation Opportunity Index V3			0.71**	0.91**				
			(0.27)	(0.21)				
Log Innovation Opportunity Index V4					0.45**	0.44**		
					(0.14)	(0.11)		
Log Innovation Opportunity Index Baseline							0.58**	0.69**
							(0.20)	(0.16)
N	147	147	147	147	147	147	147	147
Number of Clusters	49	49	49	49	49	49	49	49
Weighted	No	Base Pop.	No	Base Pop.	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (13). The 147 observations are associated with 49 states across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variable, namely the log of the Innovation Opportunity Index, is described in detail in the main text and in appendix C.4. It is a proxy for the volume of technologically intensive procedures that are delivered. As indicated in the body of the table, the specifications in columns 1, 3, 5, and 7 equally weight all observations, while the remaining columns are weighted according to each state's population during the first time period. All specifications control for state and time period fixed effects, as well as interactions between the log of non-medical patents per capita and a set of time period dummy variables. The remaining differences across columns pertain to the construction of the Innovation Opportunity Index variable. Variations in this key variable's construction are described in greater detail in Appendix C.4. As noted in Appendix C.4 and in the main text, key differences involve two issues. A first key issue involves whether one of the primary inputs is the Finkelstein (2007) measure of the baseline elderly uninsured rate versus the baseline elderly under-insured rate. Columns 1, 2, 5, and 6 use the under-insured variable while the remaining columns use the uninsured variable. The second key issue involves our assumption about the evolution of demand for technologically intensive treatments among the non-elderly. In columns 1 through 4, we treat demand from the non-elderly as a constant. In columns 5 through 8, we assume that demand from the non-elderly grows by five percentage points across each of the time periods in our sample. Standard errors account for correlation clusters across time at the state level.

Appendix Table A.3: Effects of Medicare's Introduction: Robustness of within-U.S. Estimates to Alternative Definitions of the Covered Market Share

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Dependent Variable	Medical Patenting							
Log Covered Market Share V2	0.53*	0.78**						
	(0.25)	(0.25)						
Log Covered Market Share V3			0.71+	1.04**				
			(0.39)	(0.35)				
Log Covered Market Share V4					0.72**	0.74**		
					(0.25)	(0.19)		
Log Covered Market Share Baseline							0.63**	0.73**
							(0.22)	(0.16)
N	147	147	147	147	147	147	147	147
Number of Clusters	49	49	49	49	49	49	49	49
Weighted	No	Base Pop.	No	Base Pop.	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (13). The 147 observations are associated with 49 states across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variable, namely the log of the covered market share, is described in detail in the main text and in appendix C.4. It is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1, 3, 5, and 7 equally weight all observations, while the remaining columns are weighted according to each state's population during the first time period. All specifications control for state and time period fixed effects, as well as interactions between the log of non-medical patents per capita and a set of time period dummy variables. The remaining differences across columns pertain to the construction of the Covered Market Share variable. Variations in this key variable's construction are described in greater detail in Appendix C.4. As noted in Appendix C.4 and in the main text, key differences involve two issues. A first key issue involves whether one of the primary inputs is the Finkelstein (2007) measure of the baseline elderly uninsured rate versus the baseline elderly under-insured rate. Columns 1, 2, 5, and 6 use the under-insured variable while the remaining columns use the uninsured variable. The second key issue involves whether variations are imposed as changes from a common base or whether common Covered Market Shares are assumed for the time periods corresponding with the 1970s and the 1980s. One or the other assumption is needed because only the state-level changes and the national average coverage shares are known from the data. In columns 1 through 4, we assume a constant Covered Market Share in the 1970s and 1980s and compute changes from spatially varying base levels. In columns 5 through 8, we assume a constant Covered Market Share in the 1950s and 1960s and compute changes from these constant levels to spatially varying levels in the 1970s and 1980s. Standard errors account for correlation clusters across time at the state level.

Appendix Table A.4: Effects of Medicare's Introduction: Robustness to Alternative Definitions of the Innovation Opportunity Index

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Medical Patenting							
Log Innovation Opportunity Index V2	0.72**	0.79**						
	(0.27)	(0.25)						
Log Innovation Opportunity Index V3			0.76*	0.77**				
			(0.31)	(0.24)				
Log Innovation Opportunity Index V4					0.57*	0.68*		
					(0.24)	(0.31)		
Log Innovation Opportunity Index Baseline							0.66*	0.78**
							(0.30)	(0.30)
N	336	336	336	336	336	336	336	336
Number of Clusters	56	56	56	56	56	56	56	56
Weighted	No	Base Pop.	No	Base Pop.	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (17). The 336 observations are associated with 49 states and 7 large foreign countries across 2 categories of innovation and across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variable, namely the log of the covered market share, is described in detail in the main text and in appendix C.4. It is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1, 3, 5, and 7 equally weight all observations, while the remaining columns are weighted according to each state or country's population during the first time period. All specifications control for time period-by-technology category fixed effects, state-by-technology category fixed effects, and state-by-time period fixed effects. The remaining differences across columns pertain to the construction of the Covered Market Share variable. Variations in this key variable's construction are described in greater detail in Appendix C.4. As noted in Appendix C.4 and in the main text, key differences involve two issues. A first key issue involves whether one of the primary inputs is the Finkelstein (2007) measure of the baseline elderly uninsured rate versus the baseline elderly under-insured rate. Columns 1, 2, 5, and 6 use the under-insured variable while the remaining columns use the uninsured variable. The second key issue involves our assumption about the evolution of demand for technologically intensive treatments among the non-elderly. In columns 1 through 4, we treat demand from the non-elderly as a constant. In columns 5 through 8, we assume that demand from the non-elderly grows by five percentage points across each of the time periods in our sample. Standard errors account for correlation clusters across time at the state level.

Appendix Table A.5: Effects of Medicare's Introduction: Robustness to Alternative Definitions of the Covered Market Share

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Medical Patenting							
Log Covered Market Share V2	0.59*	0.70**						
	(0.27)	(0.21)						
Log Covered Market Share V3			0.89+	0.97**				
			(0.46)	(0.37)				
Log Covered Market Share V4					0.75*	0.81*		
					(0.34)	(0.34)		
Log Covered Market Share Baseline							0.62*	0.70**
							(0.28)	(0.26)
N	336	336	336	336	336	336	336	336
Number of Clusters	56	56	56	56	56	56	56	56
Weighted	No	Base Pop.	No	Base Pop.	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (17). The 336 observations are associated with 49 states and 7 large foreign countries across 2 categories of innovation and across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variable, namely the log of the covered market share, is described in detail in the main text and in appendix C.4. It is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1, 3, 5, and 7 equally weight all observations, while the remaining columns are weighted according to each state or country's population during the first time period. All specifications control for time period-by-technology category fixed effects, state-by-technology category fixed effects, and state-by-time period fixed effects. The remaining differences across columns pertain to the construction of the Covered Market Share variable. Variations in this key variable's construction are described in greater detail in Appendix C.4. As noted in Appendix C.4 and in the main text, key differences involve two issues. A first key issue involves whether one of the primary inputs is the Finkelstein (2007) measure of the baseline elderly uninsured rate versus the baseline elderly under-insured rate. Columns 1, 2, 5, and 6 use the under-insured variable while the remaining columns use the uninsured variable. The second key issue involves whether variations are imposed as changes from a common base or whether common Covered Market Shares are assumed for the time periods corresponding with the 1970s and the 1980s. One or the other assumption is needed because only the state-level changes and the national average coverage shares are known from the data. In columns 1 through 4, we assume a constant Covered Market Share in the 1970s and 1980s and compute changes from spatially varying base levels. In columns 5 through 8, we assume a constant Covered Market Share in the 1950s and 1960s and compute changes from these constant levels to spatially varying levels in the 1970s and 1980s. Standard errors account for correlation clusters across time at the state level.

Appendix Table A.6: Effects of Medicare's Introduction: Robustness to Alternative Definitions of the Innovation Opportunity Index

Dependent Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Medical Patenting							
Log Innovation Opportunity Index V2	0.53+	0.62*						
	(0.27)	(0.26)						
Log Innovation Opportunity Index V3			0.59	0.85**				
			(0.38)	(0.32)				
Log Innovation Opportunity Index V4					0.45*	0.51*		
					(0.21)	(0.20)		
Log Innovation Opportunity Index Baseline							0.52+	0.70**
							(0.30)	(0.26)
1970s x Med. Equip. x US State	0.23	-0.06	0.19	-0.15	0.27	-0.01	0.23	-0.07
	(0.20)	(0.13)	(0.22)	(0.15)	(0.20)	(0.13)	(0.20)	(0.14)
1980s x Med. Equip. x US State	0.27*	0.10	0.23	-0.01	0.34**	0.18	0.30*	0.11
	(0.13)	(0.13)	(0.16)	(0.15)	(0.12)	(0.11)	(0.13)	(0.12)
N	336	336	336	336	336	336	336	336
Number of Clusters	56	56	56	56	56	56	56	56
Weighted	No	Base Pop.	No	Base Pop.	No	Base Pop.	No	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (17). The 336 observations are associated with 49 states and 7 large foreign countries across 2 categories of innovation and across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variable, namely the log of the covered market share, is described in detail in the main text and in appendix C.4. It is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1, 3, 5, and 7 equally weight all observations, while the remaining columns are weighted according to each state or country's population during the first time period. All specifications control for time period-by-technology category fixed effects, state-by-technology category fixed effects, and state-by-time period fixed effects. The remaining differences across columns pertain to the construction of the Covered Market Share variable. Variations in this key variable's construction are described in greater detail in Appendix C.4. As noted in Appendix C.4 and in the main text, key differences involve two issues. A first key issue involves whether one of the primary inputs is the Finkelstein (2007) measure of the baseline elderly uninsured rate versus the baseline elderly under-insured rate. Columns 1, 2, 5, and 6 use the under-insured variable while the remaining columns use the uninsured variable. The second key issue involves our assumption about the evolution of demand for technologically intensive treatments among the non-elderly. In columns 1 through 4, we treat demand from the non-elderly as a constant. In columns 5 through 8, we assume that demand from the non-elderly grows by five percentage points across each of the time periods in our sample. Standard errors account for correlation clusters across time at the state level.

Appendix Table A.7: Effects of Medicare's Introduction: Estimates Using Alternative Measures of the Medicare Shock

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Medical Patenting					
1970s x Med. Equip. x Medicare Shock ('75, (1000s))	2.01**			0.88		
	(0.62)			(0.69)		
1980s x Med. Equip. x Medicare Shock ('75, (1000s))	1.80**			1.56**		
	(0.47)			(0.51)		
1970s x Med. Equip. x Medicare Shock ('70, (1000s))		2.69*			1.35	
		(1.08)			(1.03)	
1980s x Med. Equip. x Medicare Shock ('70, (1000s))		2.28**			2.38**	
		(0.80)			(0.76)	
1970s x Med. Equip. x Baseline Uninsured			3.97			2.56
			(2.92)			(2.16)
1980s x Med. Equip. x Baseline Uninsured			3.79*			4.95**
			(1.59)			(1.37)
N	336	336	336	336	336	336
Number of Clusters	56	56	56	56	56	56
Weighted	No	No	No	Base Pop.	Base Pop.	Base Pop.
Base Period	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70	'50 to '70

Note: **, *, and + indicate statistical significance at the 0.01, 0.05, and 0.10 levels respectively. The table presents estimates of equation (17). The 336 observations are associated with 49 states and 7 large foreign countries across 2 categories of innovation and across 3 time periods, namely 1950-1969, 1970-1979, and 1980-1989. The dependent variable in each regression is the count of medical equipment and device patents per capita. Construction of the key independent variable, namely the log of the covered market share, is described in detail in the main text and in appendix C.4. It is a proxy for the fraction of all health spending that is covered by comprehensive insurance arrangements. As indicated in the body of the table, the specifications in columns 1, 3, and 5 equally weight all observations, while the remaining columns are weighted according to each state or country's population during the first time period. All specifications control for time period-by-technology category fixed effects, state-by-technology category fixed effects, and state-by-time period fixed effects. The remaining differences across columns pertain to the construction of the variable that proxies for the magnitude of Medicare's impact. In columns 1 and 2, the variable is an estimate of net Medicare spending (meaning net of what would have been covered by the elderly's insurance at baseline) as of 1975. In columns 3 and 4, the variable is an estimate of net Medicare spending (meaning net of what would have been covered by the elderly's insurance at baseline) as of 1985. In columns 5 and 6, the variable is an estimate of the fraction of each states' population that was newly covered as a result of the Medicare program. Further information on the construction of these variables can be found in appendix C.4. Standard errors account for correlation clusters across time at the state level.

B Case Studies in Medical Breakthroughs Developed by Practitioners

As noted in the main text, practitioners have played central roles in some of the most important medical innovations from the second half of the 20th century. This appendix provides additional detail regarding two such developments. In particular, we discuss breakthroughs in the treatment of blood clots and of polio.

An example of particular note is Thomas Fogarty's development of the embolectomy catheter for removing blood clots (Fogarty, 1969). Fogarty's embolectomy catheter is widely regarded as the first device invented for the purpose of minimally invasive surgery. The embolectomy catheter's development was a quintessential case of an inventor tinkering in his or her attic (Riordan, 2000). Developed while he was in medical school, Fogarty's inspiration came in part from his teenage years working as a surgical scrub technician. During that time, he had witnessed first hand the high mortality risks of the prevailing, more invasive, techniques for removing blood clots. These observations underlay Fogarty's realization that improvements would require less invasive incisions. To this problem, the embolectomy catheter proved an effective, often life saving, solution.

Another example involves the development and adoption of the use of positive pressure ventilation for treating severe cases of polio. Through the middle of the 20th century, mortality rates were high among patients infected with Bulbospinal polio. Bulbospinal polio destroys nerves within the spinal cord that are critical for breathing. Through the 1940s, the primary method for assisting the breathing of polio patients was the iron lung, a massive machine that creates negative pressure around the body to force the lungs to expand. Treatment was ineffective, however, as patients often suffocated. Between 1946 and 1948 in Los Angeles, Albert Bower and V. Ray Bennett developed key insights and equipment for improving the standard care (Trubuhovich et al., 2007). The key con-

ceptual insight was to apply positive pressure ventilation rather than negative pressure ventilation. Coupled with tweaks to existing equipment, this insight appears to have substantially reduced mortality among polio patients at Los Angeles County Hospital (Bottrell, 2017).

In 1952, during a severe Danish polio epidemic, anesthesiologist Bjørn Ibsen brought Bower and Bennett's insights to Blegdam Hospital in Copenhagen (Wertheim, 2020). Ibsen's application of positive pressure ventilation at large scale led to a dramatic decline in mortality among polio patients. In addition to helping to revolutionize treatment, the Copenhagen episode shaped medicine's future organization. Due to the epidemic's scale and Blegdam Hospital's lack of mechanical ventilator units, positive pressure ventilation was applied manually via "bag ventilation" (Wertheim, 2020). This logistical challenge required the aid of roughly 1,500 dental and medical students, who worked in shifts. After the epidemic, Ibsen was positioned to set up the first modern Intensive Care Unit (ICU), a model that would soon became commonplace in hospitals elsewhere.

C Data Appendix

Our analysis uses data from a variety of sources. This appendix begins with a discussion of the sources of our patent data, with emphasis on our use of the patent data's information on technology classification systems and inventors' residences. We next discuss the sources for our data on the geography of the physician workforce, on area-specific health spending, and on the geography of the scientific workforce.

C.1 Patent Data

Our analysis makes use of patent data from two sources. The first is the ground breaking NBER patent database (Hall et al., 2001). The second is the "Comprehensive

Universe of U.S. Patents (CUSP)" database assembled by Berkes (2018).

The NBER patent database (Hall et al., 2001) contains high quality data on key information including technology classifications and the geographic residence of each patent's lead inventor. It is not sufficient for our purposes, however, because the database begins with patents granted in 1963. Consequently, we make use of data more recently assembled by Berkes (2018), which extend back to the earliest surviving records of the U.S. Patent and Trademark Office (USPTO).[23] The NBER patent database (Hall et al., 2001) and the Berkes (2018) database are complementary for our analysis. Specifically, although the NBER patent database is more complete in its coding of geography and technology classes than the Berkes (2018) database, it is the Berkes (2018) database that makes it possible for us to analyze decades preceding the introduction of the U.S. Medicare program.

Our assembly of the patent data proceeds as follows:

- We begin by using source files from Berkes (2018) to assemble a data set containing, for each patent: the associated patent number, the first IPC classification code (ipc0), the full USPTO classification code (main_uspto), the year in which the patent was filed (fyear), the year in which the patent was granted (iyear), the county (inv_county1), full county/state fips code (inv_fips1), state (inv_state1), and country (inv_country1) of the first listed inventor.

[23] In a comparison of several recent efforts to compile data sets on the universe of U.S. patents, Andrews (2019) concludes that the database laid out in Berkes (2018) is "currently the gold standard." Additional analyses of 19th and early 20th century patents have been made possible by these data. Berkes and Nencka (2019), for example, analyze the effects of the original Carnegie Library donations on innovative activity, finding that the establishment of Carnegie Libraries had substantial effects on patenting rates. Berkes et al. (2019) use the historical patent data to analyze the rise and fall of cities. They find that diverse innovation portfolios are associated with a city's resilience to the rise and fall of particular industries, while cities with innovation in the most central fields exhibit the strongest growth over subsequent decades. A similarly historic patent data set is under analysis by Akcigit et al. (2017). The PATSTAT database maintained by the European Patent Office, as analyzed for example by Doran and Yoon (2018), enables patents granted by the U.S. Patent Office to be tracked as far back as 1899.

- We next create a variable describing whether the first inventor is located in the United States. We code this variable to equal 1 if so, 0 if the inventor has is coded as having a non-US residence, and missing if the first inventor's country code is missing in the Berkes (2018) database.

- We next merge in the variables "country," "postate," "subcat," and "nclass" from the NBER patent database.

- We then use the variable "country" from the NBER patent database to fill in country codes that were missing in the Berkes (2018) database.

- Next, we use Stata's "split" command to extract the leading digits of the USPTO codes from the variable "main_uspto." We name the resulting variable "nclass-google1" to reflect that it contains information equivalent to that in the variable "nclass" from the NBER patent database.

- Next, we augment the state postal codes from the NBER patent database to include the postal codes for earlier patents, as coded in the Berkes (2018) database. This fills in postal codes for patents granted prior to 1963, so long as the postal code is not missing in the Berkes (2018) database.

- Next, we create a variable that defines the time periods across which we divide the data. In this coding, 1 corresponds with patents filed between 1950 and 1969, 2 with patents filed between 1970 and 1979, and 3 with patents filed between 1980 and 1989.

- Next, we merge in a data set of state coding schemes that facilitate subsequent merges with data from other sources.

- Next, we merge in policy variation describing the impact of the introduction of the Medicare program. We describe the construction of these variables in a later

section of this appendix. We then execute some minor additional steps to prepare these variables for our regression analysis.

- Next, we merge in data from the Historical Area Resource File, which we describe in a later section of this appendix.

C.2 Data from the Historical Area Resource File

Our analysis makes use of a number of variables that describe the geographic distributions of physicians and other health care resources during the 1950s, 1960s, 1970s, and 1980s. These data come from the "Bureau of Health Professions Area Resource File, 1940-1990" (Health Resources and Services Administration. Bureau of Health Professions, 1994). Hereafter, we refer to this data set as the Historical Area Resource File. We extract these variables from the source data set (09075-0001-Data.txt). The source data are at the county level. To merge with state-level patent counts, we collapse the data to the state level, taking sums of all counts and taking means of variables describing income per capita and median income. Prior to collapsing, we correct a notable error in the source data, namely missing values for population counts for Los Angeles County.

Note that the Historical Area Resource File provides data on counts of physicians of various types (e.g., categorized by specialty or categorized by whether they are in primarily practicing, teaching, or research positions) in selected years. Below we enumerate the key variables we utilize and the relevant years for which they were available.

- Income: available from 1959, 1975, 1980, and 1985. Begins on .txt file columns 26714, 26709, 26684, and 26659.

- Population: available from 1960, 1970, 1975, 1980, and 1985. Begins on .txt file columns 19941, 19934, 19908, 19885, and 19861.

- Total Practicing MDs: available from 1975 and 1985. Begins on .txt file columns 01228, and 01213.
- All MDs: available from 1958, 1968, 1975, 1985, and 1989. Begins on .txt file columns 00747, 00741, 00736, 00711, and 00696.
- Total Research MDs: available from 1975 and 1985. Begins on .txt file columns 01228 and 01213.
- Total Teaching MDs: available from 1975 and 1985. Begins on .txt file columns 01193 and 01178.
- Hospital Expenditures: available from 1975 and 1985. Begins on .txt file columns 18619 and 18601.

C.3 Data from Early Reports on the Medicare Program and from the Statistical Abstracts of the United States

The list below provides additional information on the sourcing for information required to construct our variables that describe variations in the impact of the introduction of Medicare on coverage and spending across the U.S. states. The list also provides sourcing for counts of the number of scientists per capita.

- Data on the fraction of elderly individuals who were either uninsured or underinsured (meaning they did not have comprehensive insurance through Blue Cross) come from Table 1 of Finkelstein (2007)
- Data on Medicare spending by state (in millions of dollars) in 1975 were taken from Table 1.1.1, page 1-93, of "Medicare: 1974 and 1975" from Social Security Administration, Office of Research and Statistics (1977).

- Data on the number of Engineers, the number of Scientists, and the Population in each state in 1964 were taken from the 1967 edition of the Statistical Abstract of the United States. Data on the number of Chemists in each state in 1966 were also taken from the 1967 edition of the Statistical Abstract of the United States (U.S. Census Bureau, Various Years).

- Data on the number of Engineers and the number of Natural Scientists in each state in 1975 were taken from the 1977 edition of the Statistical Abstract of the United States (U.S. Census Bureau, Various Years).

C.4 Construction of Variables that Describe the Impact of the Medicare Program's Introduction

In this section we describe the variables we construct to proxy for the influxes of well-insured patients and federal dollars associated with the Medicare program. In the main text (section 5), we provided a detailed explanation of the steps taken to construct our Innovation Opportunity Index, which is the variable that most closely corresponds with the driver of *innovation by doing* in our theoretical model. The main text briefly discusses a set of alternative variables we construct as proxies for the innovation opportunities generated by Medicare's introduction. Here we describe the construction of these alternative proxies in greater detail.

Our proxies for variations in Medicare's impact are assembled using several sources. Each measure is connected to the fraction of elderly individuals who were either uninsured or underinsured at baseline. We take these initial two variables from Finkelstein (2007), as discussed in the main text. We then supplement the Finkelstein variables with additional information. Most notably, each of our proxies incorporate information on the number of elderly Medicare beneficiaries in each state. Some of our proxies make use of

additional information on either the average spending of the elderly or on state-specific spending per Medicare beneficiary.

The mathematical expression for the variable we call the Medicare Shock appears below:

$$\text{Medicare Shock}_{t,s} = \frac{\text{Elderly Uninsured Rate}_{\text{Pre-1965},s} \times \text{Medicare Spending}_{t,s}}{\text{State Population}_{t,s}} \quad \text{(C.1)}$$

The construction of the Medicare Shock can be summarized as follows. First, we multiply the baseline elderly uninsured rate (i.e., $\text{Elderly Uninsured Rate}_{\text{Pre-1965},s}$) by state-wide Medicare spending in 1975 or 1970 (e.g., $\text{Medicare Spending}_{1975,s}$ for 1975). The resulting variable is an estimate of the "shock" to spending associated with those who were uninsured prior to Medicare's introduction. We have adjusted the values of $\text{Medicare Spending}_{t,s}$ from all years for inflation so that they are expressed in 2018 dollars. These variables are set equal to 0 for observations that are associated with countries outside of the United States. Finally, the variable is divided by state population to obtain a measure of new spending normalized on a per state resident basis.

The mathematical expression for the variable we call Baseline Uninsured appears below:

$$\text{Baseline Uninsured}_{s} = \frac{\text{Elderly Uninsured Rate}_{\text{Pre-1965},s} \times \text{Medicare Enrollees}_{t,s}}{\text{State Population}_{t,s}} \quad \text{(C.2)}$$

The expression for Baseline Uninsured is structured in the same manner as the expression for Medicare Shock. The only difference is that $\text{Medicare Spending}_{t,s}$ has been replaced by $\text{Medicare Enrollees}_{t,s}$. The variable thus captures the shock to the statewide coverage rate rather than the shock to spending per state resident. We use Finkelstein's

measure of the fraction of the elderly who were underinsured to construct a similar variable we call Baseline Underinsured. The variables Medicare Shock and Baseline Uninsured are used in the analysis reported in table A.7.

Constructing the measure we call the Covered Market Share involves a somewhat more complicated sequence of steps. Our definition of the Covered Market Share is straightforward. It is simply 1 minus the share of spending that is paid for by consumers out of pocket. This is a standard variable that has been used, for example, by Finkelstein (2007) in her back-of-the-envelope calculations of the aggregate effects of Medicare on the hospital sector. We are limited by the fact that we do not have sufficient information to construct values of the Covered Market Share for each state and time period in our analysis sample. We do, however, have sufficient information to estimate state-level *changes* in the Covered Market Share from the pre-Medicare period to the post-Medicare period. We can thus fill out the panel by either assuming a set of baseline values or by assuming a set of post-Medicare values. We do this using nationwide information on the out-of-pocket share of spending from the National Health Expenditure Accounts.

Recall that we constructed the variable Baseline Underinsured to be equal to the fraction of a state's population that would be newly comprehensively covered due to the introduction of the Medicare program. Importantly, this describes Medicare's impact on the coverage rate rather than on the Covered Market Share of spending. The next step is thus to multiply either Baseline Uninsured or Baseline Underinsured by a mark-up that translates each percentage point increase in the coverage rate (driven by the Medicare program) into a change in the Covered Spending Share. That is, we can calculate

$$\Delta \text{ Covered Spending Share}_s = \text{Baseline Underinsured}_s \times \text{Elderly Spending Multiplier} \tag{C.3}$$

The variable Elderly Spending Multiplier is related to the parameter ω^O from the main text, which describes the intensity of care received by elderly individuals with comprehensive insurance coverage relative to the young. Although there are some minor conceptual differences between the relevant Elderly Spending Multiplier and the parameter ω^O, we use the same values as before. That is, when we use of Finkelstein's measure of the fraction uninsured prior to Medicare, we assume an Elderly Spending Multiplier of 2.5, and when we use Finkelstein's measure of the fraction underinsured, we assume an Elderly Spending Multiplier of 2.0.

As noted above, we can construct panel variation in the Covered Market Share in one of two ways. One approach is to add ΔCovered Spending Share$_s$ to assumed values for Covered Spending Share$_{pre-1965,s}$. A second approach is to subtract ΔCovered Spending Share$_s$ from assumed values for Covered Spending Share$_{1975,s}$. For our baseline measure of the Covered Market Share, we assume for period $p = 1$, corresponding with the 1950s and 1960s, that

$$\text{Covered Spending Share}_{1,s} = 0.55. \tag{C.4}$$

We then calculate that

$$\text{Covered Spending Share}_{p,s} = \text{Covered Spending Share}_{1,s} + \Delta\text{Covered Spending Share}_{p,s} \tag{C.5}$$

for periods $p = 2$ and $p = 3$, which correspond with the 1970s and the 1980s respectively. We then use the $log(\text{Covered Market Share}_{s,t})$ in place of $log(\frac{\Omega_{s,t}}{Pop_{s,t}})$ when estimating equation (13).

For robustness analysis, we consider three alternative measures of the Covered Mar-

ket Share, which span two dimensions. A first dimension of robustness involves the construction of Δ Covered Spending Share$_s$. While our baseline measure uses Finkelstein's measure of the fraction underinsured (with an Elderly Spending Multiplier of 2.0), two of our alternative measures use Finkelstein's measure of the fraction uninsured (with an Elderly Spending Multiplier of 2.5). A second dimension of robustness is that we can impose assumptions about Covered Spending Share$_{2,s}$ and Covered Spending Share$_{3,s}$, rather than about Covered Spending Share$_{1,s}$. When working in this direction, we then construct

$$\text{Covered Spending Share}_{1,s} = \text{Covered Spending Share}_{2,s} - \Delta\text{Covered Spending Share}_{p,s}. \tag{C.6}$$

The variation in this version of the Covered Market Share differs subtly from our baseline measure. This is because the baseline measures values for Covered Spending Share$_{2,s}$ and Covered Spending Share$_{3,s}$ include variation associated with changes in the number of Medicare beneficiaries in each state over time, which would largely be driven by demographics.

C.5 Definition of Medical Equipment Patents

We use a combination of IPC codes and USPTO technology classes to identify patents associated with medical equipment and devices. We first focus on patents with IPC codes that begin with a61; this category is titled "MEDICAL OR VETERINARY SCIENCE; HYGIENE." We then add missing patents from USPTO class 623, which corresponds with prosthetic devices, and USPTO class 378, which corresponds with x-ray and gamma-ray systems.

For all analyses that exclude pharmaceuticals, we remove the USPTO classes associ-

ated with "Drugs" and "Biotechnology." These categories include

- USPTO class 424: Drugs
- USPTO class 514: Drugs
- USPTO class 435: Chemistry
- USPTO class 800: Multi-cellular Organisms

Some of our initial analyses focus on pharmaceuticals. Our counts of pharmaceutical patents include all patents in USPTO classes 424, 514, 435, and 800.

For our analysis of the effects of Medicare, we exclude uncovered categories of health-related patents. These categories include drugs, biotechnology, optical, dental, and veterinary patents. The associated list of exclusions can be found below:

- USPTO class 351: Optics
- USPTO class 433: Dentistry
- IPC class a61d: Veterinary
- USPTO class 424: Drugs
- USPTO class 514: Drugs
- USPTO class 435: Chemistry
- USPTO class 800: Multi-cellular Organisms