Medical Practice Staffing and the Production of Office Visits

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Abstract

The 2010 Affordable Care Act conferred insurance to millions of Americans just as the baby boomer generation began to retire. As a result, many health policy analysts have raised the concern that the U.S. healthcare system is unprepared to meet growing patient demand. One potential avenue to meet this growing demand is to revisit the organization and staffing of medical practices. This study uses unique, proprietary medical practice data from 2019 to investigate the relationships between physicians, various categories of the non-physician clinical workforce, and other non-labor inputs in the production of office visits. Preliminary results suggest that the marginal productivity of some inputs has fallen over time. While many elasticity estimates match in terms of their historical classification as compliments or substitutes, their magnitude has also fallen over time. One possible interpretation of these results is that medical practices have already adapted to changes in the economic, regulatory, and technological environment in which they practice and have achieved the easy efficiency gains that were once available to them. This information is of crucial importance to policymakers as they consider different methods to increase healthcare capacity, such as strengthening graduate medical education or adjusting the scope-of-practice laws that limit the autonomy of non-physician clinical staff.

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I. Introduction

For over a decade, there has been widespread concern that the American healthcare system is unprepared to meet growing patient demand. In 2008, the Bureau of Health Professions released a report arguing that the overall demand for medical services would grow faster than the supply (HRSA 2008). A 2013 report reached the same conclusion, and numerous health policy experts and industry professionals have made similar predictions (Adam N. Hofer, Jean Marie Abraham, and Ira Moscovice 2011; Kirch, Henderson, and Dill 2012; Petterson et al. 2012; 2015; Salsberg 2013; Zhang et al. 2020; AAMC 2019). For example, Petterson et al. (2015) expect that there will be a shortage of more than 33,000 primary care physicians by 2035. In addition, other studies have suggested a nursing shortage of 918,232 by 2030 (Juraschek et al. 2019).

These predictions are based on concurrent changes occurring in the supply and demand for healthcare.[1] On the demand side, the 2010 Affordable Care Act conferred insurance to 60 million Americans just as the Baby Boomer generation began to retire (Obama 2016; Vespa, Medina, and Armstrong 2020). On the supply side, the physicians and nurses are also older and, due to increasing administrative tasks, many are suffering from burnout and working fewer hours than they did in the past (Aiken, Cheung, and Olds 2009; Juraschek et al. 2019; Rao et al. 2017; Staiger 2010). The nursing profession, which is predominately female, also suffers from high turnover, attrition related to career and family choices, and a faculty shortage in nursing schools (Aiken, Cheung, and Olds 2009).

Perhaps the clearest way to increase healthcare capacity is to increase the supply of doctors, as they are often seen as the main input in the production process for healthcare. Indeed, the 115th Congress introduced several pieces of legislation designed to increase federal support for graduate

[1] For an overview of the methods used to make these projections, see Lopes, Almeida, and Almada-Lobo (2015).

medical education (see H.R. 2267, S. 1301, and H.R. 6056). Producing more doctors, however, is a long and expensive process: a medical student must complete four years of undergraduate education, then four years of medical school, and then three to five more years of residency training, depending on the specialty (MEDPAC 2009).

As an alternative to producing more physicians, others have suggested that non-physician labor can be used more effectively. Alleviating the shortage, they say, may require greater reliance on nurse practitioners and physician assistants — staff sometimes referred to as advanced practice providers (APPs) (Auerbach et al. 2013; Sarzynski and Barry 2019). For example, Bodenheimer and Smith (2013) write that "Primary care practices could greatly increase their capacity to meet patient demand if they reallocate clinical responsibilities… to nonphysician team members and to patients themselves." Surveys of patient preferences indicate that patients may be willing to receive more care from other clinical staff (Dill et al. 2013).

Compared to nurses, APPs are more highly trained clinical staff. They carry out many tasks similar to doctors while working with them but not independently from them (Sibbald, Laurant, and Scott 2006). Numerous studies indicate APPs can provide the same quality of care as doctors when handling first-time patient encounters and treating more common illnesses (Horrocks 2002; Kurtzman and Barnow 2017; Lovink et al. 2017; Yang et al. 2018). It is worth noting that the studies described above focus exclusively on labor inputs, rather than considering both labor and non-labor inputs, such as capital or technology. Very little research has directly examined the extent to which the labor inputs of a modern medical practice (including physicians, APPs, registered nurses (RNs), licensed practical nurses (LPNs), certified nurse assistants (CNAs), etc.) as well as non-labor inputs (capital, technology) may serve as compliments or substitutes in the production of office visits.

This study estimates a production function for office visits in order to examine the complementarity and substitutability of various labor and non-labor inputs in the production process. Uwe Reinhardt was the first researcher to apply production function theory to United States office visits in this way (Reinhardt 1972). In his seminal paper, he models office visits as a function of physician time, other labor inputs, and office characteristics. His results show that offices could, at the time of his study, profitably increase their patient volume by substituting doctor time with more nurse time.

Thurston and Libby (2002) revisit Reinhardt's study using data from the 1980s and a new production function. Their chosen function, the generalized linear production function developed by Diewert (1971), is written as a series of cross-products wherein each input is separately multiplied by itself and all other inputs. These cross-product terms allow Thurston and Libby (2002) to examine complementarity in the production process. For example, of the ten input pairs they consider, they find six are complements and four are substitutes. More recent studies tend to rely on the empirical framework developed by Reinhardt (1972) and Thurston and Libby (2002), but use data from outside the United States (Olsen et al. 2013; Sarma, Devlin, and Hogg 2009).[2]

My study estimates the same production function as Thurston and Libby (2002) but uses unique, proprietary data on today's medical practices provided by the American Medical Group Association (AMGA). These data are more granular than the data used in previous studies, and the more detailed information is leveraged on both sides of the production function. First, output is measured as both patient office visits and work relative value units (RVUs, a productivity measure

[2] Older studies that use Reinhardt's production function include Brown (1988), Hurdle and Pope (1989), Gaynor and Pauly (1990), Headen (1991), DeFelice and Bradford (1997), and Conrad et al. (2002).

used by Medicare to calculate physician fees). Second, three separate models of increasing specificity are estimated for each output measure. In the first model, APPs and nurses are combined into one category in the production function. This is done so that the estimates can be easily compared to the earlier estimates from Thurston and Libby (2002). In the second model, APPs and nurses are separated into their own categories. Finally, in the third model, nurses are subdivided even further into three categories (RNs, LPNs, and CNAs).

Preliminary results using data from 2019 show that regression-based estimates of marginal productivity have declined for some inputs over time. For example, in the 1980s one additional hour of physician time was associated with one and one-third additional patient office visits per week (Thurston and Libby 2002). Now, one additional hour of physician time is associated with less than a tenth of a visit. Similarly, when nurses and APPs are combined into one category, the hiring of an additional nurse is associated with slightly more than four office visits per week. Before, the hiring of an additional nurse was associated with over seven and a half more visits (Thurston and Libby 2002). When work RVUs are used as the output measure, the results are generally similar but larger in magnitude.

The 2019 results also indicate the productive relationships between the inputs may be changing over time. If two inputs are q-complements, then the presence of one raises the productivity of the other. Alternatively, if two inputs are q-substitutes, then the presence of one lowers the productivity of the other. Input pairs which may be q-complements based on the preliminary results of this study include physician time and technicians, physician time and nurses, and APPs and LPNs. However, depending on the model, the degree of complementarity or substitutability has declined over time relative to the findings reported in Thurston and Libby (2002). Together, the results suggest that over the past 40 years medical practices have realized the efficiency gains that were once readily available.

This study provides insight into the complex relationship between various inputs into the production of office visits in a time of increased stress on the health care system. My findings should be of particular interest to medical practices as they continue to search for strategies to produce to both produce more visits and reduce costs. In addition, policymakers will want to use this information when they weigh the costs and benefits of expanding the supply of medical personnel or adjusting the laws and regulations that proscribe what work can be performed by whom.

II. Data

The data for this study come from AMGA's 2019 Medical Group Operations and Finance Survey. AMGA is a trade association representing large multispecialty medical groups. The operations and finance survey is a practice-level survey containing information on patient access, office operations, revenue and expenses, and staffing. The 2019 edition of the survey is the most recent and detailed edition available. These data will be supplemented with data from the 2020 edition upon its release.

The operations and finance survey is weighted towards the large multispecialty medical groups that AMGA serves. Unlike previous studies which focus primarily on independently owned and operated single physician practices, the unit of analysis in this study is a practice, typically employing several physicians, located within a medical group.[3] In most cases, there are multiple practices per medical group and, as mentioned, many physicians working within each practice.

[3] For example, only 12% of the physicians surveyed in the 1988 data that Thurston and Libby use are employed by a group practice.

Although the operations and finance survey does not generalize to the universe of medical practices, there is a growing trend of medical practices consolidating into larger groups (Kirchhoff 2013).

Physician survey data of this kind are extremely rare (Berk 2016). In the mid-1990s, the Healthcare Financing Administration (HCFA) discontinued its survey of physician offices. Since then, neither the Centers for Medicare and Medicaid Services (CMS, the successor to HCFA) nor any other government agency has collected similar data. This is perhaps one reason why more recent studies rely on non-U.S. data. It also explains why the study by Thurston and Libby was published in 2002 using data from the mid-1980s. AMGA is graciously providing access to their current data under a special agreement specifically written for this study.

II.A Output Measures

Two measures of medical practice output are used: total weekly patient office visits and total weekly work RVUs. The RVUs are a productivity measure used to calculate Medicare payments. In the mid-1980s, HCFA became concerned about growing Medicare costs and low reimbursement rates for primary care physicians. To help alleviate these concerns, the agency tasked Harvard economist William Hsiao to develop a new payment scheme. In response, Hsiao and his colleagues created the Resource-Based Relative Value System (RBRVS).

The system is designed such that each medical procedure is given a code (called a Current Procedure Terminology or CPT code). Each code corresponds to a certain number of RVUs of a specific type. The three types are for work effort, practice expense, and liability insurance. The Medicare payment equals the total RVU multiplied by a dollar conversion factor, which is adjusted for geographic variations in costs. The RVUs are designed to reflect the resource usage of any one service relative to the resource usage of other services. Congress did not authorize RBRVS until

1989 and the system was not fully phased in until 1992. Today, most private payers also rely on the system, and many physicians use the work RVUs to measure their productivity (Clemens and Gottlieb 2017; Smith 2015).[4]

II.B Input Measures

All three models estimated in this paper include physician time, technicians, office aids, and capital as inputs in the production process of office visits. Physician time is defined as the sum of all the hours worked per week by every physician within a given practice. This differs slightly from the earlier studies (Reinhardt 1972; Thurston and Libby 2002) wherein physician time was defined as the number of hours worked per week by the physician owner being surveyed. Even so, this previous definition still captured the total hours worked per week in practices where the physician owner was the only doctor (i.e. the vast majority of practices at the time). Moreover, for both definitions, a one-unit change in this input is interpreted as one additional hour of physician time.

Technicians refers to radiology/imaging staff and laboratory staff, and office aids includes referral coordinators, medical receptionists, and office call center staff. These labor categories were defined this way to be as similar as possible to the earlier studies. This way, any changes in the results should reflect the underlying changes in the productive relationships. All labor inputs (including APPs and nurses) are measured as the number of full time equivalent (FTE) employees normalized by the number of FTE physicians working at the office. One FTE is equivalent to 2,080 hours of paid time per year, inclusive of vacation and holiday time. Capital refers to the yearly

[4] For more information on RBRVS, see Laugesen (2014) and Smith (2015).

rental and depreciation costs of office space and equipment. All models also include as controls the number of physicians per 1,000 population and an indicator for specialty.[5]

The three models are differentiated by how APPs and nurses enter the production function. APPs refers to nurse practitioners and physician assistants. These are the most highly trained non-physician clinical staff. Generally, their autonomy varies according to state scope-of-practice laws, but in most states, they have full authority to prescribe prescription drugs. Registered nurses (RNs) are the next most highly trained staff, followed by licensed practical nurses (LPNs), and then nurses aids (hereafter referred to as certified nursing assistants or CNAs).

III. Methods

The goal of this study is to examine the extent to which the labor inputs of a modern medical practice as well as non-labor inputs may serve as compliments or substitutes in the production of office visits. To do so, this study follows the previous literature by estimating a production function for office visits. This function expresses one output as a function of one or more inputs. This relationship can be written without a specific functional form as:

$$Q = F(\boldsymbol{X}) = f[H(z), X_2, X_3, \dots, X_K] \tag{1}$$

where, in this context, Q denotes the number of office visits produced by a medical practice, $H(z)$ is the rate of input of doctor time in the practice, and the elements of the vector $\boldsymbol{X} = (X_1, \dots, X_K)$ are the quantities of other labor and non-labor inputs used at the practice.

The next step is to choose, from a menu of production functions, one that, for theoretical reasons, best describes the production process. Most of the commonly used production functions satisfy the following four properties:

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[5] The number of physicians per 1,000 population is calculated using data from the Association of American Medical College's (AAMC's) 2019 State Physician Workforce Data Report. See https://www.aamc.org/data-reports/workforce/report/state-physician-workforce-data-report.

1. *Nonnegativity:* $F(\boldsymbol{X})$ is a finite, non-negative, and real-valued number.
2. *Strong Essentiality:* $F(\boldsymbol{X})$ requires some of every input in the production process.
3. *Monotonicity:* If $\boldsymbol{X}^1 \geq \boldsymbol{X}^0$ then $F(\boldsymbol{X}^{\mathbf{1}}) \geq F(\boldsymbol{X}^{\mathbf{0}})$. In other words, additional units of an input will increase output.
4. *Concavity:* For vectors $\boldsymbol{X}^1$ and $\boldsymbol{X}^0$, and $0 \leq \theta \leq 1$, $F(\theta\boldsymbol{X}^0 + (1-\theta)\boldsymbol{X}^1) \geq \theta F(\boldsymbol{X}^0) + (1-\theta)F(\boldsymbol{X}^1)$. In other words, a variety of inputs will produce no less output than many of one type of input.

These properties are neither exhaustive nor universal. For example, property (2) is often replaced with *weak essentiality*, meaning $F(\boldsymbol{X})$ only requires at least one input. Property (3) is also often relaxed to *nondecreasing*, whereby additional units of an input will not decrease output.

To conduct my empirical analysis I use the generalized linear production function proposed by Diewert (1971), which is the same function selected by Thurston and Libby (2002). For a vector of K inputs $\boldsymbol{X} = (X_1, \ldots, X_K)$, with $X_0 = 1$, this function is defined as:

$$Y = F(X) = F(X_0, \ldots, X_K) = \sum_{i=0}^{K}\sum_{j=0}^{K} \alpha_{ij}\sqrt{X_i}\sqrt{X_j} \tag{2}$$

where $\alpha_{ij} = \alpha_{ji}$. If $\alpha_{ij} \geq 0$ for $i, j = 1, \ldots, K$ then this function is everywhere nondecreasing and satisfies every condition for a legitimate production function. Even if some $\alpha_{ij} < 0$, it may still be a valid production function so long as the negative coefficients are not too large. Most importantly, this function satisfies *weak essentiality*. This requirement was originally set by Reinhardt, as not every practice will employ every type of labor.

Since the multiplication is commutative, Equation (2) can be simplified slightly as:

$$Y = \sum_{i=0}^{K}\sum_{j=i}^{K} \beta_{ij}\sqrt{X_i}\sqrt{X_j} \tag{3}$$

where $\alpha_{ij} = \beta_{ij}$ for $i = j$ and $\alpha_{ij} = \beta_{ij}/2$ otherwise. I estimate three versions of the production function given by Equation (3), which are differentiated by how the non-physician clinical staff are categorized. Formally, the three versions are:

- Model 1: $K = 5$, $\boldsymbol{X} =$ {physician hours, nurses, technicians, office aids, and capital}.
- Model 2: $K = 6$, $\boldsymbol{X} =$ {physician hours, APPs, nurses, technicians, office aids, and capital}.
- Model 3: $K = 8$, $\boldsymbol{X} =$ {physician hours, APPs, RNs, LPNs, CNAs, technicians, office aids, and capital}.

In the first model [Model 1], APPs, RNs, LPNs, and CNAs are combined into one "nurse" category to allow for easy comparison with the previous literature (Reinhardt 1972; Thurston and Libby 2002). In the second model [Model 2], APPs are included in the production function by themselves, while RNs, LPNs, and CNAs are left combined as the "nurse" category. Finally, in the last model [Model 3], APPs, RNs, LPNs, and CNAs are included in the production function separately.

To examine q-complementarity, the Hick's elasticity of complementarity, η^H, is calculated for each input pair following Thurston and Libby (2002). For any two inputs, i, j $(i \neq j)$, the elasticity is defined as:

$$\eta_{ij}^H = \frac{Y \times F_{ij}}{F_i \times F_j} \; \forall i \neq j \tag{4}$$

where Y is the output, F_{ij} is the cross-partial for inputs i and j, and F_i and F_j are the marginal products for inputs i and j, respectively.[6] So long as the marginal products are positive $(F_i > 0)$, the sign of the elasticity is determined by the sign of β_{ij}. A positive elasticity indicates the two inputs are complements; a negative elasticity indicates the two inputs are substitutes.

[6] $F_i = \sum_{j=0}^{K} \alpha_{ij} \sqrt{\frac{X_j}{X_i}} = \beta_{ii} + \frac{1}{2}\left(\sum_{j=0}^{K} \beta_{ij} \sqrt{\frac{X_j}{X_i}}\right)$ and $F_{ij} = \frac{1}{4}\beta_{ij}\left(\frac{1}{\sqrt{X_i}\sqrt{X_j}}\right)$

IV. Results

Table 1 shows a comparison of means for the inputs. The leftmost 1965–67 column shows the values from Reinhardt (1972), while the middle two 1985 and 1988 columns show the values from Thurston and Libby (2002). The rightmost column shows the values for the 2019 AMGA data used in my analysis. Similarly, the top half of the table displays the means for the inputs that are common across all three studies, while the bottom half displays the means for the inputs unique to my analysis.

Starting at the top of Table 1 and reading from left to right, the average number of hours worked per week by a single physician appears to have declined from the mid-1960s to the mid-1980s. Other research has shown this trend continuing into the present (Rao et al. 2017; Staiger 2010). However, in this study, the average number of hours worked by a single physician is 40 by definition, since this is based on the number of FTE physicians reported at a given practice. To be consistent with how the previous literature (Reinhardt 1972; Thurston and Libby 2002) measure physician time, I multiply the number of reported FTE physicians by 40 hours. Moving down, Table 1 also shows that physician offices have become more capital intensive over time. Likewise, if APPs, RNs, LPNs, and CNAs are added together into one category, then physician offices have also become more nurse intensive. The number of technicians appears to have remained constant, while the number of office aids increased through the 1980s before falling again.

Tables 2, 3, and 4 report the regression results for Models 1, 2, and 3 described above for both office visits and work RVUs. It is difficult to interpret the regression coefficients directly because of the square root transformation and cross-products. As a result, the remainder of this section focuses on the marginal product and elasticity estimates based on these regression coefficients rather than the coefficients themselves.

Table 5 presents a comparison of the marginal products and Hick's Elasticity estimates based on the regression coefficients from Model 1. The top panel reports estimates from Thurston and Libby (2002). The middle and bottom panels report estimates using the 2019 AMGA data. The middle panel shows the results when the outcome is office visits while the bottom panel shows the results when the outcome is work RVUs. Standard errors are calculated using the "delta method." If two inputs are complements, then the elasticity will be greater than zero. Alternatively, if two inputs are substitutes, then the elasticity will be less than zero.

In the 1980s, one additional hour of physician time was associated with more than one additional office visit per week. Now, a physician hour is associated with less than a tenth of a visit. While it may be the case that physicians have become less productive over time, the smaller marginal product for physician time may also be a mechanical result of large offices employing multiple physicians. That is, suppose that an office employs ten physicians, meaning a one unit increase in physician time would be measured as a change from 400 to 401 hours. Perhaps this change is simply less meaningful than a change from 40 to 41 hours, which would be the more common case in the older data when offices were more likely to be owned and operated by a single physician.

A comparison of the top and middle panels in Table 5 shows that the marginal products for nurses and technicians have also declined, although at 4.15 and 4.75, respectively, these estimates are still reasonable. However, hiring one more office aid is now associated with a loss of four visits per week. If we look down at the elasticity estimates, we can see that the estimate for office aids and capital is large and negative (η^H = -6.39). It could be that the negative marginal product for office aids and the large negative elasticity between them and capital reflect an increasing administrative burden. For example, increased use of health IT systems which may not communicate well with each other and which may be cumbersome to use could be reducing the contribution of office aids towards total physician output. Another possibility is that office aids are expending large amounts of time and energy obtaining prior authorization from insurance companies and, should reimbursement be denied after a treatment has been performed, pursuing bad denials.

For most other input pairs, the sign of the elasticity has remained unchanged, meaning complements remain complements and substitutes remain substitutes for the most part. For example, Thurston and Libby (2002) find strong q-complementarity between physician time and nurses (η^H = 1.97, p<0.01). In the 2019 data for office visits, this elasticity is much smaller and not statistically significant (η^H = 0.12). The one exception to this trend of smaller elasticities is for physician time and technicians, which is large and significant (η^H = 1.55, p<0.05), implying the two inputs are strong complements. This could be due to more tests being available today than in the 1980s or physicians practicing medicine more defensively to forestall medical malpractice lawsuits. Looking at the results that use the 2019 data for work RVUs (the bottom panel), the marginal products and elasticities exhibit the same pattern as the results produced using office visits.

One interpretation of these results is that since the mid-1980s, medical practices may have already adjusted the size and skill mix of their clinical workforce and made other changes to achieve the efficiency gains that were once readily available to them. The marginal products are therefore lower and the elasticities between some inputs are smaller. These changes may have been driven by the rise of managed care and its use of capitated payments. Note that many of the 2019 elasticity estimates are not statistically significant. Incorporating more data from AMGA in the near future should improve the precision of these estimates and produce more statistically significant results.

Table 6 presents the results for Model 2 where APPs and nurses enter the production function as separate categories. The top panel of Table 3B presents the results for when output is measured as total visits and the bottom panel presents the results when output is measured as total work RVUs. Here, the results show nurses provide practices with more marginal visits than APPs (15.02 vs. 7.52) but contribute fewer work RVUs than APPs (22.45 vs. 27.8). This may reflect the fact that APPs have their own fee schedule under the RBRVS and directly contribute to their office's total RVU count, whereas nurses operate in a purely supporting role.

Interestingly, the marginal products for technicians and office aids have changed sign in the results for total visits. Employing one more technician is now associated with 11 fewer patient visits per week but hiring an additional office aid is associated with an increase of four visits per week. These changes in sign are likely a reflection of the nature of APP work. Depending on state scope-of-practice laws, APPs may be performing a great deal of work in the office but are unable to order tests and scans – only the physician can do that. Similarly, the tasks carried out by APPs may be less subject to change than treatments rendered by physicians, and so office aids may not need to spend so much time acquiring prior authorization and pursuing bad denials.

The elasticity estimates in Table 6 are generally small and insignificant, which is consistent with the estimates shown in the previous table. Once again, it should be noted that the addition of more data could adjust these estimates and tighten the standard errors, thereby producing more statistically significant results. Currently, though, the elasticity for physician time and APPs is positive and significant (η^{H}= 0.97, p<0.01), which suggests these inputs are strong complements and work well together. This is also likely caused by state scope-of-practice laws, as physicians must be in a supervisory role with their APPs, although the degree of supervision can vary by state.

Table 7 presents the results for Model 3 where nurses are further subdivided into RNs, LPNs, and CNAs. The panels in this table are organized the same way as in Table 3B. Here, APPs and LPNs exhibit roughly equal marginal products (8.92 and 9.93, respectively, for total visits), while RNs show the smallest marginal product (0.34 for total visits) and CNAs show the largest (19.81 for total visits). At first glance, these results may seem surprising, as CNAs are the least skilled nurses. However, CNAs are the nurses who will take a patient's temperature, weight, and blood pressure upon entering the office. The marginal product for CNAs is likely higher than the rest because they will do this for every patient, regardless of any patient's particular illness. As for the other nursing occupations, one possibility is that the tasks that have traditionally fallen to RNs have shifted to APPs and LPNs.

The elasticity estimates are consistent with the interpretation that APPs and LPNs may be taking on more work previously done by RNs. If we look at the results for total visits, we can see that the elasticity for physician time and APPs is still positive and significant (η^H = 0.67, p<0.01). However, the elasticity for APPs and LPNs is also positive and significant (η^H = 0.17, p<0.05), which suggests the two inputs are strong complements that work well together and are productivity enhancing. As is the case in the earlier tables, the marginal products and elasticities for work RVUs show the same pattern as the results for total visits.

V. Discussion

This paper investigates the productive relationships between different labor and non-labor inputs in the production process for office visits using unique, proprietary data on medical practices from 2019. Given the increased stress placed on the healthcare system by the influx of patients insured under the Affordable Care Act and the aging population, it is important to understand how each input contributes to the production of office visits and whether opportunities exist to better optimize across inputs.

In the model where more and less highly trained nurse staff enter the production function as one group, my preliminary results suggest the contribution of each input may have diminished to some degree since the mid-1980s. For example, one additional hour of physician time, one additional nurse, and one additional technician are all associated with fewer additional office visits than they were 40 years ago. Similarly, more office aids are associated with fewer office visits. Models that have each nurse type enter the production function separately show a wide range of nurse contributions to the production process, whether output is measured by office visits or work RVUs. In these models, more technicians are associated fewer visits but more work RVUs, while more office aids are associated with more visits but a fewer number of RVUs.

The elasticity estimates also hint at changing workplace dynamics. Here, the preliminary results suggest complementarity between physician time and technicians, between physician time and APPs, and between APPs and LPNs. In many cases, however, the degree of complementarity or substitutability between inputs appears to have lessened over time as many of the 2019 elasticity estimates are close to zero. One possible explanation for these results is that, in response to the rise of managed care and capitated payments, medical practices have grown more efficient over the past four decades.

The results presented here have an immediate, practical application in the discussions surrounding healthcare capacity and workforce shortages. Namely, we can imagine a hypothetical medical practice that must meet its obligation to patients, but which operates in an environment where there are worker shortages. If the practice were to lose a worker of some kind, we could trace out different alternative input combinations that would maintain the same level of output as before the worker left. The following scenario is an illustrative example based on the preliminary results.

Suppose the hypothetical practice has quantities of inputs that correspond to the sample averages. Since there are many health policy professionals forecasting a shortage of physicians, let’s imagine the number of physician hours at the practice is cut in half from 333 to 166. To maintain production of the same number of office visits, the practice could increase the number of APPs from about one to about three or increase the number of CNAs from around one to around six. If the practice were to substitute with capital, annual spending on capital would need to increase by 34 percent (from about $450K to about $600K). If the number of physician hours were to fall by 40 (representing the loss of one FTE physician), the practice could hold output constant by increasing the number of CNAs from one to four.

The exercise above illustrates how the results of this sort of analysis can be applied. While this analysis is based on my preliminary results, the final version of this study will likely differ in at least three important ways. First, the inclusion of 2020 data should roughly double the existing sample and may modify the current estimates and standard errors, improving precision. Second, the AMGA data also contain worker salaries. Incorporating this information will allow for a full-blown cost-benefit analysis, which will also show which input combination can maintain the same patient volume and be profitable to employ. Finally, the AMGA data contain counts of FTE employees that will be added to the analysis. Specifically, the technician category might be expanded into a broader “clinical support staff” category that also consists of pharmacy staff, nutritionists, and behavioral health staff. Likewise, the office aids category might be expanded to include quality assurance personnel. Finally, counts of FTE administrative staff will also be added to the analysis to investigate the productive capacity of administrators.

VI. Conclusion

Using unique, proprietary data from 2019, this study estimates a production function for office visits in order to examine the complementarity and substitutability of various labor and non-labor inputs in the production process. The inputs considered include physician time, the number of FTE workers of different types, and capital, which is measured as the rental and depreciation costs of office space and equipment. Production function regression coefficients are used to calculate Hick's Elasticities for different pairs of inputs, which show which combinations are q-complements (and therefore efficiency enhancing) and which are q-substitutes (and therefore not efficiency enhancing).

Preliminary results suggest that the marginal productivity of some inputs is smaller than their marginal productivity from several decades ago (Reinhardt 1972; Thurston and Libby 2002). While many elasticity estimates match in terms of their historical classification as compliments or substitutes, their magnitudes have also fallen over time. One possible interpretation of these results is that medical practices have already adapted to changes in the economic, regulatory, and technological environment in which they practice and have achieved the easy efficiency gains that were once available to them.

Today, the healthcare system must respond to the sharp increase in the demand for medical care brought on by the influx of newly insured patients under the Affordable Care Act and the aging population. As policymakers contemplate how to increase healthcare capacity, they should take a wholistic view and consider options that encompass the entire production process for medical care. This way, they can help make sure the health care sector is maximizing the amount of care produced while at the same time minimizing cost.

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Table1: Comparison of Means

Variable	1965–67	1985	1988	2019
Common Inputs				
Physician Time	34.12	25.28	25.28	40.00[a]
Capital	$464	$35,433	$55,304	$455,000[b]
RNs	0.46	0.33	0.35	0.55
Technicians	0.26	0.29	0.49	0.51[c]
Office Aids	1.24	1.53	1.74	0.87[d]
New Inputs				
APPs				1.03
LPNs				0.82
CNAs				1.13
All Nursing Staff including APPs				2.40
All Nursing Staff excluding APPs				1.88

Note: [a] Physician time is defined as the total number of hours worked per week by every physician at the office. It is calculated by multiplying the number of FTE physicians working at an office by 40. [b] Capital values for 1965–67, 1985, and 1988 are adjusted for inflation to 2019 dollars. [c] Technicians does not include pharmacy staff, dietician/nutritionists, behavioral health/social work staff, and other direct patient care support staff. [d] Office aids does not include quality assurance personnel.

Table 2A: Regression Results from Model 1

	Total Visits		Total wRVUs	
	Coefficient	Std. Error	Coefficient	Std. Error
Constant	8.283	(9.840)	0.558	(16.678)
$1 \times \sqrt{H}$	0.685	(1.746)	2.372	(3.552)
$1 \times \sqrt{L_1}$	-4.146	(8.560)	-4.262	(15.366)
$1 \times \sqrt{L_2}$	-1.124	(6.491)	-18.111	(17.949)
$1 \times \sqrt{L_3}$	4.285	(4.674)	32.887***	(11.209)
$1 \times \sqrt{K}$	-1.637	(1.202)	-3.358	(2.757)
$\sqrt{H} \times \sqrt{H}$	0.051***	(0.009)	0.093***	(0.026)
$\sqrt{H} \times \sqrt{L_1}$	0.192	(0.722)	0.083	(1.364)
$\sqrt{H} \times \sqrt{L_2}$	0.872	(0.638)	2.313	(1.427)
$\sqrt{H} \times \sqrt{L_3}$	-1.295*	(0.663)	-3.191**	(1.453)
$\sqrt{H} \times \sqrt{K}$	-0.001	(0.012)	-0.002	(0.032)
$\sqrt{L_1} \times \sqrt{L_1}$	-0.287	(1.242)	-0.680	(2.524)
$\sqrt{L_1} \times \sqrt{L_2}$	-0.858	(1.234)	0.254	(4.202)
$\sqrt{L_1} \times \sqrt{L_3}$	-2.561	(2.118)	-5.264	(4.276)
$\sqrt{L_1} \times \sqrt{K}$	0.825*	(0.465)	1.466	(1.003)
$\sqrt{L_2} \times \sqrt{L_2}$	2.334	(1.652)	4.609	(5.055)
$\sqrt{L_2} \times \sqrt{L_3}$	-1.708	(2.086)	-5.264	(6.789)
$\sqrt{L_2} \times \sqrt{K}$	-0.448	(0.292)	-0.200	(0.548)
$\sqrt{L_3} \times \sqrt{L_3}$	1.728	(1.599)	-0.962	(3.515)
$\sqrt{L_3} \times \sqrt{K}$	0.669	(0.399)	0.453	(0.836)
$\sqrt{K} \times \sqrt{K}$	-0.005*	(0.003)	-0.001	(0.006)
N	870		853	

Note: Inputs are defined as H: physician time; L_1: nurses; L_2: technicians; L_3: office aids; and K: capital. Nurses includes APPs, RNs, LPNs, and CNAs. Standard errors are heteroskedastic robust and clustered at the office level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2B: Regression Results from Model 2

	Total Visits		Total wRVUs	
	Coefficient	Std. Error	Coefficient	Std. Error
Constant	19.951**	(8.234)	28.186*	(14.191)
$1 \times \sqrt{H}$	0.842	(1.569)	2.573	(3.273)
$1 \times \sqrt{L_1}$	-16.504**	(7.493)	-42.540**	(18.041)
$1 \times \sqrt{L_2}$	-0.505	(7.790)	8.782	(14.800)
$1 \times \sqrt{L_3}$	-2.097	(7.802)	-22.678	(19.870)
$1 \times \sqrt{L_4}$	5.165	(6.173)	25.381**	(11.119)
$1 \times \sqrt{K}$	-2.289	(1.386)	-4.735	(3.131)
$\sqrt{H} \times \sqrt{H}$	0.042***	(0.012)	0.070**	(0.028)
$\sqrt{H} \times \sqrt{L_1}$	1.684**	(0.787)	3.558**	(1.625)
$\sqrt{H} \times \sqrt{L_2}$	-0.685	(1.055)	-1.849	(1.892)
$\sqrt{H} \times \sqrt{L_3}$	0.813	(0.613)	2.353	(1.491)
$\sqrt{H} \times \sqrt{L_4}$	-1.085**	(0.484)	-2.459**	(1.085)
$\sqrt{H} \times \sqrt{K}$	0.010	(0.014)	0.025	(0.032)
$\sqrt{L_1} \times \sqrt{L_1}$	4.226*	(2.232)	9.433*	(5.166)
$\sqrt{L_1} \times \sqrt{L_2}$	1.785	(2.455)	5.392	(5.017)
$\sqrt{L_1} \times \sqrt{L_3}$	1.570	(1.657)	2.651	(3.857)
$\sqrt{L_1} \times \sqrt{L_4}$	0.073	(1.645)	-1.277	(3.461)
$\sqrt{L_1} \times \sqrt{K}$	-0.292	(0.386)	0.007	(0.835)
$\sqrt{L_2} \times \sqrt{L_2}$	-3.395	(2.342)	-9.032	(6.113)
$\sqrt{L_2} \times \sqrt{L_3}$	-1.232	(1.750)	0.475	(4.748)
$\sqrt{L_2} \times \sqrt{L_4}$	-2.564	(3.194)	-3.093	(3.968)
$\sqrt{L_2} \times \sqrt{K}$	1.523*	(0.839)	2.581	(1.784)
$\sqrt{L_3} \times \sqrt{L_3}$	4.675*	(2.300)	11.580	(7.645)
$\sqrt{L_3} \times \sqrt{L_4}$	-1.994	(2.333)	-6.173	(7.517)
$\sqrt{L_3} \times \sqrt{K}$	-0.617*	(0.336)	-0.680	(0.693)
$\sqrt{L_4} \times \sqrt{L_4}$	0.161	(1.701)	-0.790	(3.429)
$\sqrt{L_4} \times \sqrt{K}$	0.609*	(0.317)	0.240	(0.677)
$\sqrt{K} \times \sqrt{K}$	-0.007**	(0.003)	-0.005	(0.007)
N	808		791	

Note: Inputs are defined as H: physician time; L_1: APPs; L_2: nurses; L_3: technicians; L_4: office aids; and K: capital. Nurses includes RNs, LPNs, and CNAs. Standard errors are heteroskedastic robust and clustered at the office level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 2C: Regression Results from Model 3

	Total Visits		Total wRVUs	
	Coefficient	Std. Error	Coefficient	Std. Error
Constant	14.453*	(7.169)	11.112	(15.206)
$1 \times \sqrt{H}$	0.994	(1.423)	2.779	(2.903)
$1 \times \sqrt{L_1}$	-17.862**	(6.750)	-43.342***	(15.092)
$1 \times \sqrt{L_2}$	3.183	(3.162)	2.425	(10.408)
$1 \times \sqrt{L_3}$	1.681	(6.354)	16.874	(12.590)
$1 \times \sqrt{L_4}$	-5.128	(4.930)	-1.282	(11.023)
$1 \times \sqrt{L_5}$	-2.745	(6.952)	-22.433	(19.324)
$1 \times \sqrt{L_6}$	4.124	(5.156)	17.133*	(8.826)
$1 \times \sqrt{K}$	-2.285*	(1.232)	-4.818*	(2.701)
$\sqrt{H} \times \sqrt{H}$	0.041***	(0.010)	0.069***	(0.023)
$\sqrt{H} \times \sqrt{L_1}$	1.689**	(0.769)	3.658**	(1.543)
$\sqrt{H} \times \sqrt{L_2}$	-0.082	(0.422)	1.014	(1.279)
$\sqrt{H} \times \sqrt{L_3}$	-0.090	(0.640)	-1.719	(1.491)
$\sqrt{H} \times \sqrt{L_4}$	-1.420	(1.193)	-3.889	(3.049)
$\sqrt{H} \times \sqrt{L_5}$	0.517	(0.558)	1.571	(1.513)
$\sqrt{H} \times \sqrt{L_6}$	-0.725*	(0.402)	-0.928	(1.058)
$\sqrt{H} \times \sqrt{K}$	0.014	(0.013)	0.030	(0.026)
$\sqrt{L_1} \times \sqrt{L_1}$	3.996*	(2.293)	8.924*	(4.748)
$\sqrt{L_1} \times \sqrt{L_2}$	2.866	(2.416)	6.956*	(3.526)
$\sqrt{L_1} \times \sqrt{L_3}$	3.043*	(1.517)	4.594	(3.701)
$\sqrt{L_1} \times \sqrt{L_4}$	-1.439	(1.732)	-2.759	(3.941)
$\sqrt{L_1} \times \sqrt{L_5}$	0.812	(1.545)	0.440	(3.050)
$\sqrt{L_1} \times \sqrt{L_6}$	-0.511	(1.334)	-1.835	(2.867)
$\sqrt{L_1} \times \sqrt{K}$	-0.155	(0.370)	0.184	(0.788)
$\sqrt{L_2} \times \sqrt{L_2}$	-0.579	(1.725)	-0.242	(4.804)
$\sqrt{L_2} \times \sqrt{L_3}$	-2.566**	(1.063)	-4.714	(2.965)
$\sqrt{L_2} \times \sqrt{L_4}$	-1.407	(2.270)	-4.158	(5.187)
$\sqrt{L_2} \times \sqrt{L_5}$	-0.023	(1.476)	6.444	(6.207)
$\sqrt{L_2} \times \sqrt{L_6}$	-1.695	(2.019)	-2.513	(2.960)
$\sqrt{L_2} \times \sqrt{K}$	0.089	(0.243)	-0.747	(0.641)
$\sqrt{L_3} \times \sqrt{L_3}$	-2.474	(1.730)	-9.073**	(4.196)
$\sqrt{L_3} \times \sqrt{L_4}$	-4.121	(2.518)	-7.362	(7.152)
$\sqrt{L_3} \times \sqrt{L_5}$	0.036	(1.908)	-1.769	(5.440)

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	Total Visits		Total wRVUs	
	Coefficient	Std. Error	Coefficient	Std. Error
$\sqrt{L_3} \times \sqrt{L_6}$	-2.158	(2.157)	-3.912	(3.302)
$\sqrt{L_3} \times \sqrt{K}$	0.696	(0.473)	1.941	(1.317)
$\sqrt{L_4} \times \sqrt{L_4}$	-0.530	(1.588)	-2.581	(3.625)
$\sqrt{L_4} \times \sqrt{L_5}$	-3.428*	(1.962)	-7.811	(7.390)
$\sqrt{L_4} \times \sqrt{L_6}$	-1.052	(2.343)	1.020	(4.820)
$\sqrt{L_4} \times \sqrt{K}$	2.051**	(0.952)	4.137	(2.481)
$\sqrt{L_5} \times \sqrt{L_5}$	5.451***	(1.834)	13.274*	(7.282)
$\sqrt{L_5} \times \sqrt{L_6}$	2.676	(2.646)	5.417	(3.392)
$\sqrt{L_5} \times \sqrt{K}$	-0.588*	(0.334)	-0.462	(0.663)
$\sqrt{L_6} \times \sqrt{L_6}$	1.021	(1.499)	2.199	(3.417)
$\sqrt{L_6} \times \sqrt{K}$	0.322	(0.271)	-0.813	(0.633)
$\sqrt{K} \times \sqrt{K}$	-0.010**	(0.004)	-0.009	(0.006)
N	808		791	

Note: Inputs are defined as H: physician time; L_1: APPs; L_2: RNs; L_3: LPNs; L_4: CNAs; L_5: technicians; L_6: office aids; and K: capital. Standard errors are heteroskedastic robust and clustered at the office level.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3A: Elasticity Estimates for Model 1

		1985, 1988 Samples — Total Visits				
Marginal		Physician Time	Nurses	Technicians	Office Aids	Capital
Productivity F_i		1.34	7.42	10.75	6.17	0.17
Hicks Elasticity η^H	Nurses	1.97***				
		(0.76)				
	Technicians	1.42	-7.87			
		(1.21)	(6.25)			
	Office Aids	0.28	3.17*	-2.19		
		(0.55)	(2.82)	(2.65)		
	Capital	-2.94***	-0.43	5.11***	0.08	
		(0.06)	(12.91)	(0.07)	(1.69)	
		2019 Sample — Total Visits				
Marginal		Physician Time	Nurses	Technicians	Office Aids	Capital
Productivity F_i		0.06	4.15	4.75	-3.97	-0.005
Hicks Elasticity η^H	Nurses	0.12				
		(0.28)				
	Technicians	1.55**	-0.25			
		(0.76)	(0.45)			
	Office Aids	1.58	0.51	0.94		
		(1.33)	(0.41)	(1.54)		
	Capital	0.04	-4.96	7.47	-6.39	
		(0.43)	(9.34)	(14.78)	(16.10)	
		2019 Sample — Total wRVUs				
Marginal		Physician Time	Nurses	Technicians	Office Aids	Capital
Productivity F_i		0.12	6.69	18.11	-15.51	-0.02
Hicks Elasticity η^H	Nurses	0.03				
		(0.45)				
	Technicians	0.93***	0.02			
		(0.35)	(0.34)			
	Office Aids	0.93	0.32	0.34		
		(0.87)	(0.27)	(0.37)		
	Capital	0.02	-2.55	0.38	-0.54	
		(0.27)	(4.43)	(0.87)	(0.93)	

Note: Hick's elasticities of complementarity, η^H, are calculated at the means of the data. Standard errors are calculated by the "delta method" and are in parentheses. For $\eta^H > 0$, the inputs are complements, and, for $\eta^H < 0$, the inputs are substitutes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3B: Elasticity Estimates for Model 2

		Total Visits					
Marginal		Physician Time	APPs	Nurses	Technicians	Office Aids	Capital
Productivity F_i		0.07	7.52	15.02	-11.06	4.40	0.005
Hicks Elasticity η^H	APPs	0.97***					
		(0.26)					
	Nurses	-0.11	0.07				
		(0.39)	(0.10)				
	Technicians	-0.50	-0.22	0.05			
		(0.48)	(0.22)	(0.07)			
	Office Aids	-1.05	0.02	-0.16	0.46		
		(1.47)	(0.35)	(0.28)	(0.55)		
	Capital	0.35	-2.22	3.35	5.05	7.78	
		(0.83)	(5.86)	(2.55)	(10.11)	(12.46)	
		Total wRVUs					
Marginal		Physician Time	APPs	Nurses	Technicians	Office Aids	Capital
Productivity F_i		0.16	27.80	22.45	0.68	-10.73	-0.02
Hicks Elasticity η^H	APPs	0.49***					
		(0.14)					
	Nurses	-0.18	0.07				
		(0.57)	(0.07)				
	Technicians	19.78	2.81	0.36			
		(228.37)	(32.45)	(4.43)			
	Office Aids	0.81	0.05	0.09	15.63		
		(0.75)	(0.15)	(0.14)	(186.58)		
	Capital	-0.17	-0.01	-1.57	35.06	0.49	
		(0.27)	(0.71)	(3.38)	(415.01)	(0.91)	

Note: Hick's elasticities of complementarity, η^H, are calculated at the means of the data. Standard errors are calculated by the "delta method" and are in parentheses. For $\eta^H > 0$, the inputs are complements, and, for $\eta^H < 0$, the inputs are substitutes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3C: Elasticity Estimates for Model 3

		Total Visits							
		Physician Time	APPs	RNs	LPNs	CNAs	Technicians	Office Aids	Capital
Marginal Productivity F_i		0.07	8.92	0.34	9.93	19.81	-8.36	2.35	0.05
Hicks Elasticity η^H	APPs	0.67***							
		(0.24)							
	RNs	-1.15	5.65						
		(12.32)	(29.06)						
	LPNs	-0.04	0.17**	-5.08					
		(0.28)	(0.08)	(28.22)					
	CNAs	-0.24	-0.03	-1.19	-0.10				
		(0.50)	(0.04)	(6.34)	(0.07)				
	Technicians	-0.31	-0.07	0.07	-0.003	0.12			
		(0.37)	(0.13)	(4.54)	(0.16)	(0.08)			
	Office Aids	-1.18	-0.12	-13.81	-0.50	-0.10	-0.92		
		(1.59)	(0.32)	(88.00)	(0.63)	(0.24)	(1.06)		
	Capital	0.05	-0.07	1.45	0.32***	0.40	0.41	0.61	
		(0.04)	(10.39)	(10.39)	(0.11)	(0.32)	(0.47)	(0.53)	
		Total wRVUs							
		Physician Time	APPs	RNs	LPNs	CNAs	Technicians	Office Aids	Capital
Marginal Productivity F_i		0.15	29.40	-7.48	29.38	42.22	-1.53	-16.24	-0.06
Hicks Elasticity η^H	APPs	0.50***							
		(0.13)							
	RNs	-0.63	-0.49						
		(1.19)	(0.62)						
	LPNs	-0.27	0.08	0.39					
		(0.47)	(0.31)	(0.59)					
	CNAs	-0.31	-0.02	0.17	-0.08				
		(0.78)	(0.03)	(0.31)	(0.08)				
	Technicians	-6.14	-0.20	12.92	0.91	1.98			
		(38.84)	(1.94)	(80.82)	(5.45)	(11.35)			
	Office Aids	0.21	0.05	-0.29	0.12	-0.02	4.01		
		(0.27)	(0.07)	(0.45)	(0.11)	(0.07)	(24.81)		
	Capital	0.08	0.06	1.02	0.68***	0.72	3.98	0.41	
		(0.07)	(0.22)	(1.83)	(0.12)	(0.75)	(26.44)	(0.51)	

Note: Hick's elasticities of complementarity, η^H, are calculated at the means of the data. Standard errors are calculated by the "delta method" and are in parentheses. For $\eta^H > 0$, the inputs are complements, and, for $\eta^H < 0$, the inputs are substitutes. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$