The Effect of Physician Group Mergers on the Health Outcomes of Medicare Beneficiaries*

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Abstract

We measure the effect of different types of physician mergers on the health outcomes of Medicare beneficiaries. Our analysis considers how such transactions affect the progression of hypertension and diabetes into worse health states. We find that horizontal mergers lead to economically and statistically significant increases in the likelihood of transitioning to a worse health state. In contrast, mergers that combine different specialties can be associated with better health outcomes. We document variation in the magnitude of these effects depending on measures of the competitiveness of local markets.

Key words: Vertical integration; horizontal merger; merger efficiencies; physicians; antitrust

JEL Codes: I11, L23, L40

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I Introduction

In recent years, a host of research has demonstrated that the nature of physician practice organization has changed (Burns et al., 2013). In particular, the average size has grown substantially. For example, the American Medical Association's annual survey suggests that the proportion of physicians working in practices with fewer than five physicians fell by almost 5 percentage points between 2012 and 2018, while the proportion working in practices with at least 25 physicians grew by 3 percentage points (Kane, 2018).

The welfare implications of large physician practices are unclear. On the one hand, consolidation could lead to more efficient care. For example, if there were large fixed costs to adopting helpful new technologies (e.g., electronic medical records), then having a broader base of physicians to spread the expense over could quicken adoption. Similarly, if larger practices tend to involve physicians drawn from a variety of specialties, larger practices could enable better care coordination. However, the ongoing consolidation of physician practices could also be leading to welfare losses. If the growth in the average practice stemmed from horizontal mergers, it could lead to higher prices and/or worse health outcomes for patients. Alternatively, if there are meaningful diseconomies of scale or scope, then the growth of practices could be worsening outcomes even in the absence of a loss of competition.

The ambiguous consequences of consolidated physician practices have led to a growing body of empirical research. However, to date, little consensus has been reached due to challenges associated with the measurement of both outcomes and provider integration. This paper advances the literature by exploiting rich data that allow us to surmount both of these hurdles. Specifically, we consider the impact of different physician practice mergers of thousands of doctors, on a variety of health outcomes related to healthcare utilization and health outcomes among Medicare patients.

In the spirit of Walden (2016), we identify physician group mergers using the MD-PPAS, which reports the primary and secondary TAX ID (i.e., group identifier) for each provider. By following providers, and observing changes in the TAX IDs they are associated with, we are able to plausibly identify mergers. The large number and variety of our observed transactions allow us to explore mechanisms through which consolidation may impact social welfare. In particular, we stratify transactions by whether they involve combinations of physicians within specialty (i.e., horizontal) or across specialty (vertical or, potentially, unrelated). In addition, we further explore multiple mechanisms that may impact physician group merger consequences by allowing their effects to vary depending on the level of competition in local markets.

Health care outcomes measurement poses its own challenges. Commercial prices are hard to observe, and may be confounded with drivers of the organizational variables whose impact is at issue. Treatment quality is difficult to measure and observe in many contexts, and notably so in healthcare where easily observable outcomes like death may be rare. We address this problem by exploiting rich patient treatment history data that allow us to consider patients' progression through various health states relating to either diabetes or hypertension. We focus on these two diagnosis categories since they are prevalent (particularly within our sample population) and treatable. The prevalence of these direct outcome measures gives us greater power than infrequently observed outcomes, like mortality, while also not being subject to potential biases associated with utilization-based measures, such as readmissions, that may confound clinical effects with changes in financial incentives.

We bring our rich outcomes and organizational change data together in a number of different empirical specifications that enable us to address potential confounding factors such as patient demographic characteristics, patient health, treatment trends, provider utilization, and provider characteristics. This careful approach to identification reduces the possibility that our results are driven by a failure to control for unobservable confounders or selection bias.

Our analyses find that mergers that combine physicians from the same specialty have economically and statistically significant negative effects on patient health. For example, we find that patients whose primary care doctor is acquired by a practice already offering primary care services have higher likelihood of various negative health outcomes than the population mean. Some of these effects are worse if the transaction takes place in a geographic area where primary care physicians are already concentrated in just a few practices.

However, we find that not all increases in physician practice size have negative effects on consumer welfare. In particular, we find that when primary care physicians are acquired by groups containing other types of physician that the likelihood of negative health outcomes declines. These effects are of the same approximate absolute magnitude as the negative ones of horizontal mergers. When stratifying by the level of competition in the local primary care provider market, we find that these vertical efficiencies can vary with the degree of local specialty concentration.

We extend several veins of the literature on the industrial organization of health care markets (Gaynor et al., 2015). First, our work furthers the small but rapidly growing literature on competition in physician markets. Prior contributions have shown that many local markets have grown meaningfully more concentrated in recent years (Capps et al., 2017a). Other work has exploited sharp changes in market structure to show that this often leads to higher prices paid for the care of commercially insured patients (Dunn and Shapiro, 2014, Koch and Ulrick, forthcoming). However, little was known about how such changes translated to patient care quality. Using a rigorous identification approach, our paper shows that horizontal mergers can meaningfully reduce the value of patient care received by Medicare beneficiaries. This is consistent with the findings of Koch et al. (forthcoming), which considers how concentration among cardiology practices affects various health outcome and utilization measures.

Second, our paper contributes to the literature assessing the consequences of combining different types of health care provider within financially integrated organizations. Much of this literature focuses on combinations of hospitals and physicians (Post et al., 2017, Koch et al., 2017, Capps et al., 2018, Koch et al., 2018). However, a few recent papers focus on the impact of multispecialty practices. As in our own work, Baker et al. (2019) find that Medicare patients who receive care from multispecialty practices tend to have better health outcomes.

II Data

Our analysis combines ambulatory and hospital claims from Medicare during the 2005-2012 period with the MD-PPAS data. We describe these respective sources below.

II.1 Identifying physicians involved in mergers and acquisition

To understand when doctors switch firms, we begin by characterizing how we identify where doctors work in the first place. The MD-PPAS is a data set that assigns medical providers to medical practices and descibes each provider's specialty. The main provider identifier is an NPI, which is an assigned number used in medical billing. Medical practices are identified via tax identification numbers (TINs), which assign where the reveneue for each medical claim goes. The assignment of national provider identifier (NPI) to practice (TIN) is according to the TIN for which the majority of that NPI's Medicare revenue went to. This method is a variation of that described in Walden (2016).

The MD-PPAS also assigns each provider (NPI) a primary specialty classificaiton. This classification is initially disaggregated (GP, Family practice, Cardiology, etc.) per CMS's Provider Enrollment, Chain, and Ownership System (PECOS) files and each NPI's billing behavior. (Many types of claims identify provider specialty.) The MD-PPAS also aggregates medical specialty into several broad categories: primary care (GP and Family practice, among others); medical specialty, such as cardiology and gastroenterology; surgical specialy (orthopedist, e.g.); and five other categories. We will focus on primary care, medical specialties and surgical specialties.

To identify when mergers of provider groups might occur we do the following: stack the MD-PPAS data across available years, and generate bins that correspond to the number of doctors within each specialty (either narrow or broad, depending upon the specification) that was assigned to a pair of TINs in year t and year t+1. The resulting data set is a TIN-to-TIN transition matrix. For example, suppose that there is a GP group whose nine doctors all remain in the same TIN in years t and t+1. This pattern will create one bin, with the same TIN for each of the two years, and a count of nine in the data.

Now suppose that five of the doctors leave to a different TIN in year t+1. This data pattern will create two observations in the matrix: the first with same TIN for year t and year t+1, and a count of four; and a second observation with the original (same as the first) TIN for year t, and a different TIN for the year t+1 TIN, with a count of five. If these three providers joined an existing practice, there will be other observations with the second TIN in each of the year t and t+1 that characterize how doctors from other practices joined and left that practice.

These transition matricies are separately calculated by specialty type of the provider. We do this to allow the matrix to account for the differentiation across providers by specialty, and the implications of this differentiation for the size and scope of the practice. For example, if a primary care provider joins an existing multi-specialty practice, this changes the practice in two ways: it increases the scale of the primary care it provider; it does not not change the scale of the specialty care it provides; but does adjust by the extent of the scope across specialties that it provides. Thus, by separating out the TIN-to-TIN transitions separately by specialty type allows to to distinguish between changes in scale differently across specialties; and augmentations to the returns to scope that might be available to firms shifting the mix of provider types within an organization.

A graphical representation of the procedure can be found in Figure 1.

This procedure allows us to measure and characterize providers moving across practices. In fact, with every transition, two practices are transformed: the one that lost the providers and the one that gained them. This procedure also allows us to differentiate between practices that absorbed providers and those that lost them; and, in turn, to understand how each of these different organizational transitions might have different effects for patient health.

Not all TIN-to-TIN transiitions reflect substantial changes to a practice's organizational structure. In order to separate out the minor adjustments from the substantial adjusments, we create two rules that distinguish between minor and major changes to a practice's presence within a specialty. First, looking at all of the doctors within a specialty and TIN in year t, we say that there was a merger from that group within a specialty if more than half of them are assigned to a different TIN in year t+1. Whether the leaving providers all go to one other practice or each go to a different (new practice) is not reflected in this "merger to" assignment. The TIN transition example from before triggers this rule since mroe than half (5/9) of the GPs left the practice to join a new practice.

Alternatively, we capture the absorption of a substantial number of providers in a specialty by assigning a "merger from" rule. The "merger from" indicator turns on when fewer than ninety percent of the providers within a specialty at a TIN in year t+1 were also working at that TIN in the previous year. E.g., in the three doctors leaving a TIN example from before, if the TIN they join has fewer than 27 GPs that stayed in the practice from year t to year t+1.

Each of these decision rules (one half for doctors leaving a practice; ten percent for new doctors joining a practice) are chosen parsimoniously and can be adjusted in future research. Figures 3 describe the empirical distributions of how providers flow to and from TINs. Due to privacy concerns, we omit the bins that correspond to 10 or fewer providers. These figures demonstrate substantial variation in the size of the groups of NPIs leaving and going to TINs over time.

Figure 4 plots the fraction of the doctors in a TIN in year t+1 that were in that same TIN in year t, for all specialty-TINs and those flagged by the merger rule. For reference, any group where this number is less than ninety is said assigned absorbing, merger-from status. This demonstrates that most specialty-TINs do not demonstrate substantial absorption of new NPIs year-over-year. However, when they do, there is substantial variation of the relative magnitude of the number of providers previously in and not-in the specialty-TIN.

Figure 5 reports the HHI for the departures and absorptions of NPIs within a specialty. An HHI is the sum of the square of the shares. E.g., if all of the doctors remain in a TIN, the HHI for both the first year TIN and the second year TIN are 1. If half of the doctors in an original TIN remain in the TIN and half switch TINs, then the transition HHI of the doctors in the original TIN is $0.5^2 + 0.5^2 = 0.5$. If a third of the NPIs in a TIN come from the same TIN, but two thirds arrived from a distinct TIN, then the HHI is $\frac{1}{3}^2 + \frac{2}{3}^2 = \frac{5}{9}$.

The figures in the left column are the HHI for all specialty-TINs, and demonstrate that most specialty-TINs remain together, and most specialty-TINs are made up of providers that had been together. The figure in the right column correspond to the same HHIs, restricted to those TINs that trigger the merger rules. The HHIs for "merger-to" TINs has a large mass near 1; that is, when more than half of the NPIs within a specialty-TIN change TINs, they tend to do so collectively. The HHIs for the absorbing TIN that trigger the "merger-from" indicator demonstrates more heterogeneity among the absorbing firm. The ratio of new doctors to existing doctors when the existing TIN absorbs new doctors varies substantially across the many flagged absorbing TINs.

These decision rules focus on changes for practice size within a specialty. That is, they reflect changes in horizontal scale, but do not address potential changes to a practice's scope across specialties. We create further indicators for each TIN-year that cross-match the merger-to and merger-from indicators across specialties. E.g., $v_{1_2}^{from}$ is equal to one if the provider is in primary care and the TIN for which they work in year t acquired a large (at least ten percent new) number of medical specialists from other practices. These indicators allow us to understand the effects of changes to scope within a practice, both when practices lose those providers (cross-mergers from) and and when practices gain them (cross-mergers to).

This assignment generates a large number of mergers in the MD-PPAS. A histogram of the number of doctors within a specialty that are in a bin where a merger is indicated can be found in Figure2. This histogram uses the broad specialty characterization provided in the MD-PPAS. Due to data security limitations, TIN transitions with fewer than ten doctors are not reflected in the histogram, though they will be included in the merger indicators. A merger that involves multiple specialties will be reflected multiple times in this histogram, according to the number of providers within each specialty that change TINs.

These rules determine whether or not a provider was exposed to a change in practice. In order to understand the effects of these changes on the health outcomes of patients, we need to map between providers and patients. We do this in a similarly parsimonious way: if a beneficairy saw a provider exposed to one of the horizontal or vertical changes in practice scale/scope, the indicator turns on for that patient year. In order to make sure that the control group for each of the mergers-to and merger-from specifications is clean of the effects of the merger efffects of the other (e.g., patients seen by doctors absorbed by a group should not be in the control group for patients seen by doctors who were absorbed into a group), the respective control groups do not include beneficiaries seen by the other, respective merger group.

II.2 Measuring Market Concentration

To address the possibility that effects vary depending on the competitiveness of patients' local physician market, we construct "adjusted" measures of the standard Herfindahl-Hirschman Index (HHI) of market concentration. The approach of adjusting HHIs has become a standard one in the literature (Zwanziger et al., 1990, Kessler and McClellan, 2000, Dunn and Shapiro, 2014, Capps et al., 2017b). Our adjusted measure is similar to the traditional HHI (sum of squared shares times 10,000) but involves several discrete steps designed to take account of institutional characteristics of health care markets.

We begin by identifying all outpatient claims for services delivered by different physician specialties. For each observation, we observe the TIN of the provider associated with the claim. With this information, we construct HHIs based on different measures of utilization for patients living in each zip code in each year. As discussed in Kessler and McClellan (2000), these zip-code-level HHIs may not be good predictors of the level of competition that patients within a zip-code are exposed to. This is because the HHIs imply that individual physician groups differentiate their behavior based on the residences of patients. This seems unlikely.

To address this problem, we put our original zip code HHIs through two additional steps. First, physician group specific HHIs are constructed for each TIN by weighting the zip-code HHIs of their patients by their share of the physician group's total patient pool. Second, the physician-level adjusted HHIs are converted back to the patient zip-code level by weighting each physician group adjusted HHI by the proportion of patients within the zip-code that frequented that physician group. These adjustments produce measures that vary within and across patient zip codes over time. They plausibly capture the competitive pressure on the physicians available to patients within the zip code being focused upon. Patients in zip codes with higher adjusted HHIs are choosing amongst providers drawing patients from markets with few desirable options. Conversely, patients in zip codes with low adjusted HHIs can select from physicians that draw their patients from zip codes where there are many available choices.

II.3 Health conditions and outcomes

We consider health outcomes that enable us to measure the effects of physician acquisitions on provider treatment for diabetes and hypertension. While mortality is one of our outcomes of interest, we do not limit our analysis to it because it is only rarely observed and may be weakly related to ambulatory care. The prior literature acknowledges both the benefits and concerns of mortality as an analytical measure and addresses these issues by considering mortality alongside alternative outcomes. In particular, the literature extensively uses hospital utilization metrics, such as ER visits and readmissions, as alternative outcomes (see **?**) since they are more prevalent than mortality and are likely related to firm quality outcomes such as health and healthcare costs.

Unfortunately, hospital utilization measures are only indirect measures of health since they measure the services used to treat a diagnosed medical condition rather than the condition itself. In some settings, this is a desired attribute since the metric implicitly captures both clinical health and resource intensity. However, in our setting, this attribute threatens our identification since we want to isolate the clinical benefits associated with integration. Utilization-related metrics may be confounded by the fact that Medicare's provider-based billing (PBB) policies may interact with acquisitions to change the financial incentives for choosing whether to treat patients in a hospital or an office (Dranove and Ody, 2016, Koch et al., 2017, Forlines, 2017). If so, these utilization measures could confuse the clinical benefits associated with acquisitions with the changed financial incentives they also cause. Therefore, we employ a set of outcome measures that are severe and verifiable, similar to mortality, but are more prevalent and more closely related to ambulatory care, similar to hospital utilization. However, unlike hospital utilization, our outcomes are independent of PBB and do not suffer from the potential conflation of interpretations that those metrics may invite. We construct our alternative metrics using the detailed data on beneficiaries' health histories contained in the Medicare data we exploit.

We believe our most credible measures relate to diabetes. Table **??** provides the descriptions for the 5-digit ICD-9 codes that we use as diabetes outcome metrics, 250.00-250.93. In our analysis, and in Table **??**, we categorize the ICD-9 codes as either "symptomatic" or "asymptomatic."[1] These codes explicitly identify conditions that are related to the progression of diabetes. For example, the description for 250.10-250.13 is not simply "ketoacidosis," but rather "diabetes with ketoacidosis." In addition to providing a relationship between the outcome and the underlying chronic condition, we note that the existence of the code suggests that providers monitor this complication in order to assess the progression of diabetes. Indeed, the Agency for Healthcare Research and Quality (AHRQ) uses readmissions associated with these ICD-9 codes as quality measures in other applications. Overall, the explicit relationship between the underlying chronic condition and the complication that follows from it is ideal for relating health outcomes to changes in treatments that arise from changes in provider ownership.

We also use the ICD-9 diagnosis codes to identify health outcomes related to hypertension progression. We consider "any" acute cardiac condition, which we define as 5-digit ICD-9 diagnosis codes that are not defined as "chronic" by the National Household Interview Survey (NHIS) and are in the "conditions of the circulatory system" chapter heading of the ICD-9 code list.[2] We replicate the NHIS table of chronic conditions as Table **??**. We identify patients as having ischemic heart disease and heart attacks, or acute myocardial infarctions (AMI),

[1] We categorize the conditions based on the descriptions. "Symptomatic" complications have descriptions that suggest that the patient likely observes the condition (e.g., blindness). The "asymptomatic" conditions typically relate to the patient's blood sugar levels, but may be unknown to patient monitoring their bloodwork.

[2] The relevant ICD-9 codes in the chapter covering circulatory conditions range from 390-459.

using the beneficiary summary files. We also use the summary files to identify whether a beneficiary died.

The validity of the health outcome metrics rely on accurate, detailed, and consistent coding by the healthcare claims processors. If claims reporting is strategic, then using these metrics may lead to biased estimates of merger effects. For example, some of our metrics rely on physician diagnoses. If an acquisition results in increased monitoring and thus more diagnoses, our health outcome measure might suggest that acquisitions result in worse health when, in fact, the acquisition resulted in better monitoring and more diagnoses.

We believe we can provide robustness by contrasting the results for our granular health metrics with those for mortality and acute myocardial infarction (AMI), which represent severe outcomes with obvious symptoms that are unlikely to be coded inconsistently across claims processors. Moreover, these outcomes are unlikely to be disproportionately observed as a result of increased physician monitoring.[3] These conditions have also been used extensively by the previous literature in a variety of contexts.

We treat all of our health conditions as absorbing states for the beneficiary. Individuals observed with a health outcome are defined as having the condition for the rest of the sample period regardless of whether the contemporaneous period contains a claim with the ICD-9 diagnosis listed. We impose this restriction for all health outcomes, including acute conditions. In addition, we omit data from 2005 from our analysis, limiting the analysis to the period 2006 - 2012, so that we can have an entire year of observed claims to determine the health conditions and (potentially) outcomes of beneficiaries observed in 2006.

[3] We argue that our "symptomatic" diabetes metric has a similar property since it involves symptoms obvious to the patient, such as vision impairment or tingling in the extremities.

III Results

IV Across all competitive conditions

In order to assess the effect of medical practice changes on the health outcome of beneficiaries, we run regressions of the following form:

$$
\begin{aligned}
o_{i,t} = \eta_{PCP} h_{i,t}^{PCP} + \eta_{MS} h_{i,t}^{MS} + \beta_{PCP,MS} v_{i,t}^{PCP,MS} + \beta_{MS_PCP} v_{i}^{MS,PCP} \\
+ \gamma \Gamma_{i,t} + \epsilon_{i,t},
\end{aligned}
$$

where $o_{i,t}$ is beneficiary i's health outcome in period t. Depending upon the health outcome under study, we condition inclusion in this regression on pre-existing health outcome. E.g., when looking at deterioration of diabetes into one of two clinical categories, we condition on the beneficiary having lower-acuity diabetes to start, and not having experienced these higher-acuity outcomes in the past. That is, we take the higher-acuity outcomes as an absorbing state.

The main regressors of interest are those related to changes in the horizontal and vertical scope and scale of pratice. Horizontal mergers are indicated by the h_d^s variables, which are equal to one if that patient saw a doctor that was in a practice (i.e., TIN) that experienced a horizontal, within-specialty s change in practice scale, in direction d, where $d = to$ if enough providers left the practice, or $d = from$ if enough providers joined the practice. We also include indicators for non-horizontal, or vertical, changes in practice scope. We assign $v_d^{s,s'} = 1$ if a beneficiary saw a provider in specialty s whose practice experienced a change in scope with respect to specialty type s' in direction d.

We separately estimate the merger effect η by direction d. That is, we estimate this equation first for those practices losing providers, and compare that to patients who did not see a provider at a TIN that absorbed a practice. Alternatively, when we estimate the effects of absorbing practices, we drop those patients who saw a practice that lost a substantial number of providers, i.e., the opposite-direction merger identifier is turned on.

We control for a variety of patient-specific characteristics in $\Gamma_{i,t}$: age-in-years-by-gender dummies, three-digit zip code fixed effects, and relevant co-morbidities. We report standard errors clustered at three-digit ZIP code level.

The co-morbidities and other fixed effects should substantially control for patient health. However, the very act of seeing a provider in a particular specialty may itself reflect underlying health status beyond our controls. To account for this, a beneficiary must have one visit with provider of the relevant specialty to be in the control group. E.g., when we consider the effect of GP acquisitions, all beneficiaries in the control group had a medical claim with a GP.

The horizontal merger indicators turn on when a horizontal relationship between same-specialty providers changes: providers leave a horizontal relationship (merger to) join a new to horizontal relationship (merger-from). These indicators turn on at the practice level.

The cross-specialty, vertical estimates require more careful interpretation. These indicators also turn on at the group level; when a primary care provider leaves a practice with non-surgical specialists (i.e., a vertical relationship is broken), then the merger-to indicator for primary care (in the first subscript) and non-surgical specialists (in the second subscript), the merger-to indicators turns all for all of the patients that saw a primary care providers at that practice. When a primary care provider joins a practice that has non-surgical specialists, a vertical relationship is created, possibly replacing one at the primary care provider's old practice. The merger-from indicator for primary care (first subscript) and non-surgical specialist (second subscript) turns on if a patient saw a primary care provider at the practice that has a new vertical relationship. The merger-from indicator turns on if the patient saw the non-surgical specialist with a new vertical relationship. We control for a patient seeing a practice that had each of the horizontal and vertical mergers possible in the specialty-by-specialty pairs. We only report for the horizontal and vertical merger effects of primary care and non-surgical specialty, since those are most relevant to our outcomes of interest. However, we do want to account for the creation or destruction of other provider-organization patterns associated with these specific types of mergers, since these changes could confound the effect of the our main relationships of interest.

The estimates of the main specification are reported in Tables 1 and 2. The general pattern is that horizontal mergers of primary care and non-surgical specialists are associated with diminished health outcomes. These estimates are estimated with some statistical precision, particularly for the estimates of the effects of practices absorbing new doctors, as those samples are larger. (Practices that absorb providers are larger than those that lose providers, leaving more beneficiaries in the control group.) The magnitude of the effects of practices absorbing practices are smaller than those for practices losing providers. This is consistent with the absorbing practices being larger, and the exposure of patients to the disruption of such changes (or competitive harm) being more diffuse across a large absorbing group, than a smaller group losing some (or all) of its providers.

The patterns of horizontal merger estimates are stronger in the hypertensive population, where changes in physician practice are associated with increases in ischemic heart disease, AMI, other severe complications from hypertension, and mortality. The magntiude of these estimate range from five to ten percent of the underlying incidence of the outcomes. One notable exception is the relationship between horizontal mergers and glaucoma outcomes; these estimates tend to be negative, though not with much statistical precision.

The estimated effects of the vertical mergers vary a bit more. The negative sign on the vertical coefficient for primary care provider tell us that seeing a primary care provider that has a new vertical relationship with a medical specialist is associated with better health outcomes than being in the control group. This suggests that vertical efficiencies within a multi-specialty group can benefit patient health.

The coefficient for seeing a medical specialist that has a new vertical relationship with a primary care provider is negative. Here, the associated indicator turns on when the specialist is the provider with the new vertical (upstream) relationship. If a group acquisition has transitional costs, such as switching EHRs or increased administrative burden, then we might expect the consequences of this inefficiency to be widespread across the nature of the vertical-horizontal relationship between providers. That said, the benefits to integration may be asymmetric: if being in a multispecialty clinic helps a primary care provider's patient get more efficient care from medical specialists, this should be reflected in the first vertical coefficient (primary care to medical specialist). The second vertical coefficient (medical specialist to primary care) may not reflect such efficiencies, since the flow of patients to medical specialist has already been determined and the patient is unlikely to switch specialists in response to the re-arrangment of the upstream relationship.

V Separately by competitive condition

The mechanism(s) behind the results described in the previous section are not made clear by the results so far. In order to understand the potential role of competition (or lackthereof) in these effects, we stratify these regressions separately by the concentration of relevant providers that a patient might see. E.g., the effect of a merger may not be due to the loss of competition associated with the merger if the merger begins with and leaves the market unconcentrated. Alternatively, the effects of a merger that substantially increases market concentration may be due, at least in part, to the loss of competition.

Histograms of HHIs by provider types are provided in Figure 6. We construct these market concentrations using different definitions of specialty than in the regressions above. Specialties were aggregated for the regressions to account for broad, general patterns of co-integration between primary care provider, medical specialists, and surgical specialists, among others. As mentioned above, this means that some of the mergers identified as within-broad specialty are likely non-horizontal since, e.g. cardiologists and oncologists are unlikely to compete. However, the different narrow specialties of primary care (general practice, family practice, etc.) may well actually compete. Thus, we construct the HHI for those narrow specialties aggregated by the MD-PPAS as primary care, but define providers according to their unaggregated, narrow specialty for all other kinds of providers.

Primary care markets tend to be unconcentrated, as made clear by Figure 6. This is due in part to the fact that in the MD-PPAS, roughly seventy percent of family practice providers are assigned a singleton TIN; family practice providers make up around forty percent of doctors assigned to the primary care group. Other specialties demonstrate much more variation in their underlying provider concentration. E.g., the histograms of HHIs in cardiology (studied in Koch et al. (forthcoming)) substantially covers the support from zero to one. The histograms of HHIs in other specialties are provided for demonstrative purposes. Given the health conditions under consideration here, we focus on concentration in primary care and cardiology.

It may also be the case that due to a variety of circumstances (some potentially causal, some potentially confounding), the underlying probability of health outcomes varies by concentration level. This will be reported below, as we will report the mean outcome within a bin when reporting merger effects. To aid in this illustration, we also present the relationship between patient health outcomes and their respective specialty HHIs in a series of bin scatters that can be found in Figures 8, 7, and 9. These bin scatters reflect the relationship between patient health outcomes and market concentration, once accounting for the beneficiary characteristics included in the regressions. One set of bin scatter plots include three-digit ZIP code fixed effects, while another set does not. This can help characterize how much the underlying relationship is due to level differences three-digit ZIP code level.

The patterns on display are generally upward sloping: that is to say, patients who live in markets with greater provider concentration (either primary care or cardiology) experience lesser health outcomes. This pattern holds whether or not we account for fixed, persistent differences across three-digit ZIP codes, though accounting for increases the noise in the relationship. These patterns are consistent with the findings in Koch et al. (forthcoming).

The three exceptions are the relationships between (1) transitions into the first cluster of diabetic complications and glaucoma among the diabetic population, and primary care concentration, and (2) the transition into ischemic heart disease among the hypertensive, and cardiologist concentration. These patterns are both made noisier when three-digit ZIP fixed effects are accounted for. Even without those fixed effects, the negative relationship (concentration's association with better health) levels off as the concentration measure move beyond the levels (between 0.15 and 0.25) where anti-trust authorities are advised to exercise more scrutiny of mergers and acquisitions.

While we have removed some co-morbidities, patient demographic characteristics, and static geographic differences, there may be other confounding patterns. Markets with increases in primary care concentration may also be markets with increases in vertical alignment with specialists, such as opthamologists. This vertical alignment could improve the care provided to mitigate glaucoma. This is consistent with the lack of an effect of horizontal primary care mergers on glaucoma outcomes.

V.1 Estimates Separately by Market Concentration

We organize beneficiaries into four separate bins according to the measure of concentration of primary care. The thresholds used to create the bins were chosen to evenly distribute the beneficiaries into each of the bins, to maximize the power within each of the bins. The thresholds are reported in Table 3. We also report the sample mean of the health outcome within each bin.

The first panel reports the estimated effect of mergers for complications of hypertension. Two patterns stand out: first, the effect of primary care mergers diminishes with more concentrated markets; second, the benefit of seeing a provider who newly integrated with a specialist also diminishes with more concentrated markets. These patterns are not as evident for AMI and IHD, but the vertical patterns re-appears for mortality. This suggests that the effects of concentration in one specialty can have consequences for the effects of mergers and other conduct in related, downstream market. Given the putative tradeoff described so far (gains due to re-arranging provider ownership and vertical alignment vs. costs of rearranging), this flow of consequences should not be surprising.

VI Conclusion

Si requiris conclusionum, circumspice.

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Figure 1: Using TINs and specialties to identify changes in scale and scope within and across specialties.

Year t

TIN	NPI	Specialty
1234	a	GP
1234	b	GP
1234	c	GP
1234	d	Cardio
4567	e	GP

+

Year t+1

TIN	NPI	Specialty
1234	a	GP
4567	b	GP
4567	c	GP
1234	d	Cardio
4567	e	GP

↓

Transition Matrix

TIN at t	TIN at t+1	Specialty	NPIs	Horizontal?
1234	1234	GP	1	To
1234	4567	GP	2	To, From
1234	1234	Cardio	1	No
4567	4567	GP	1	From

Figure 2: Size of clusters of NPIs Going to a New Specialty-TIN. Histogram does not report cell sizes fewer than ten.

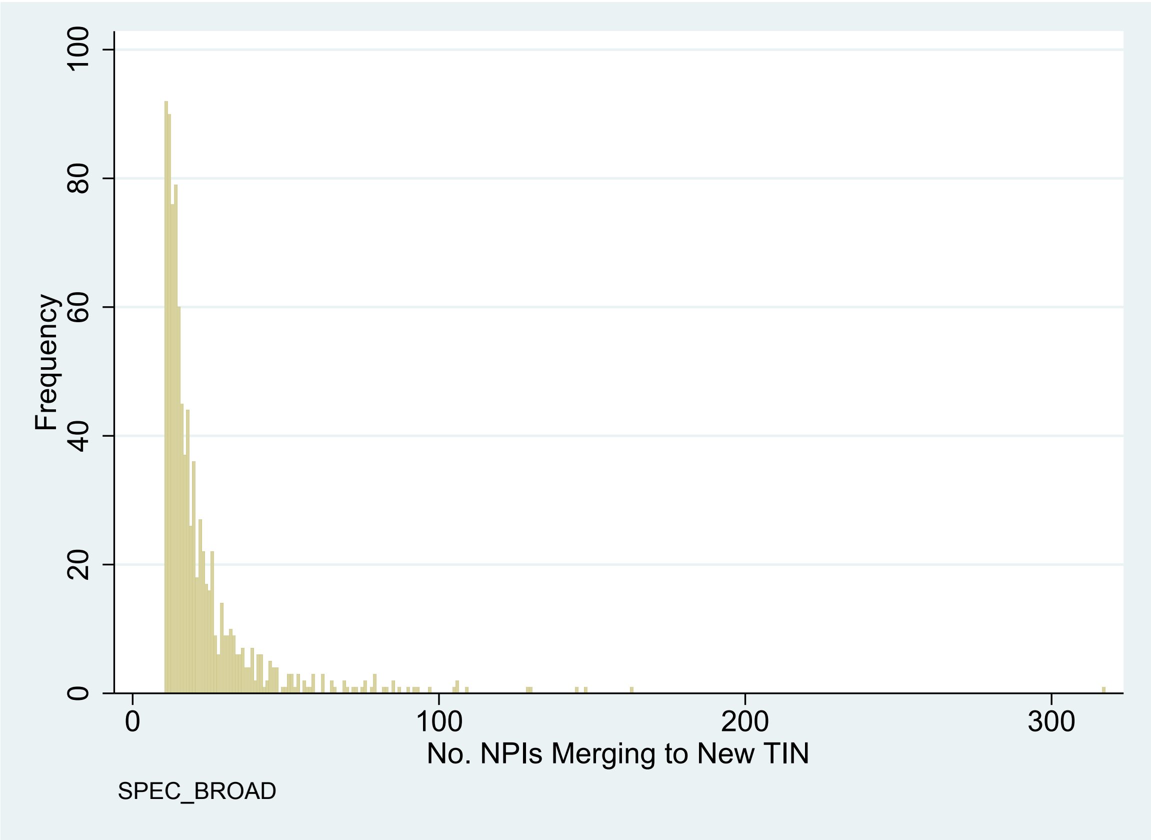
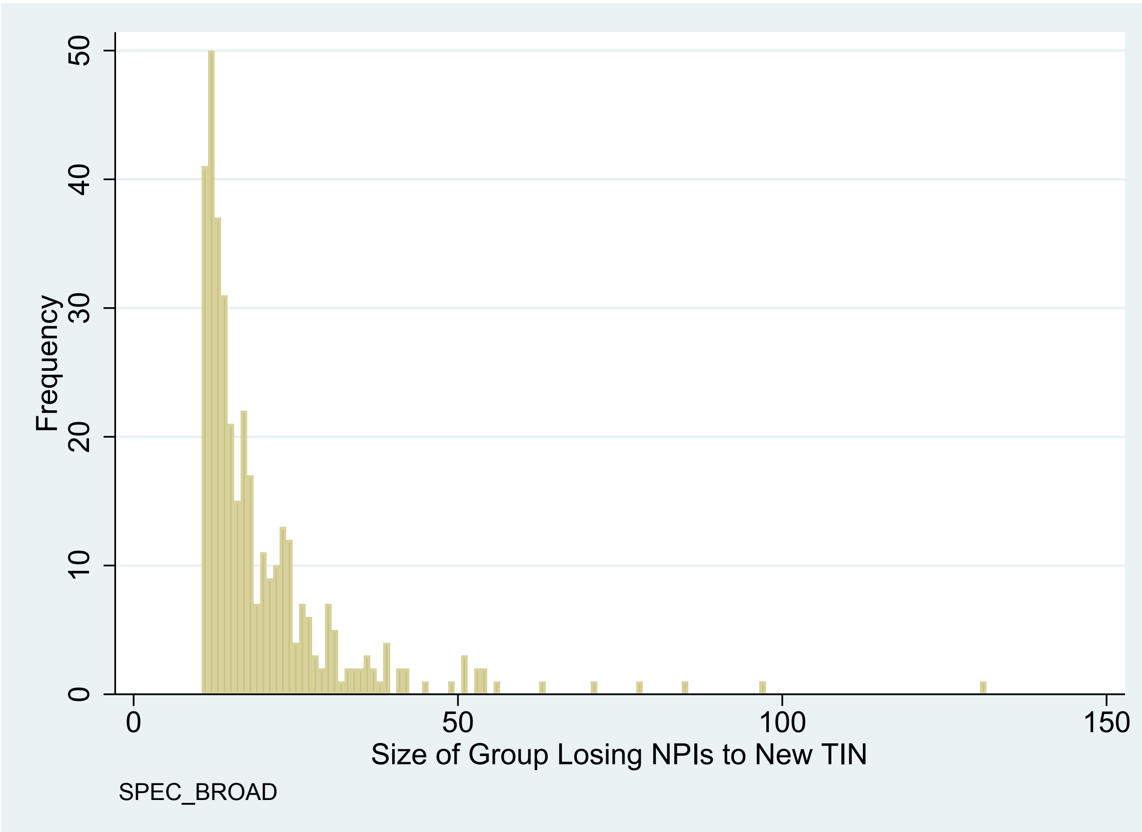


Figure 3: Specialty-Group Sizes of Specialty-Groups Losing, Absorbing Providers. Histograms do not report cell sizes fewer than ten.



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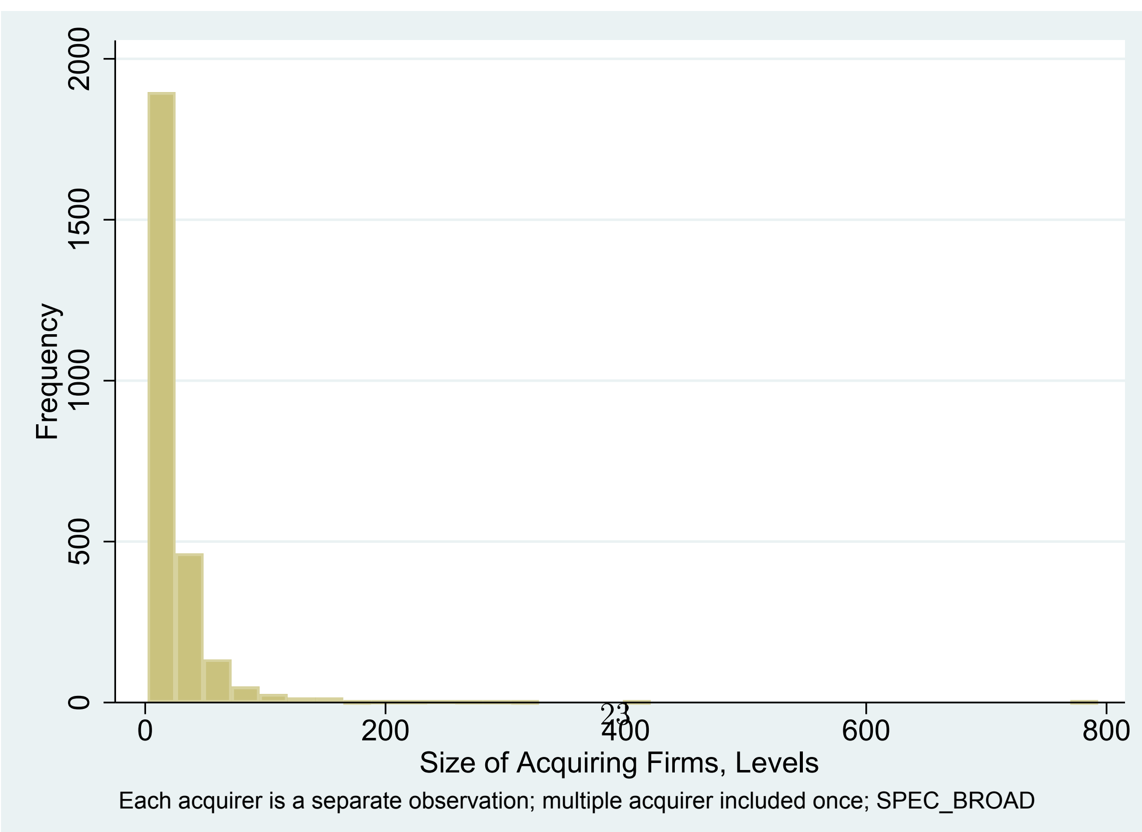

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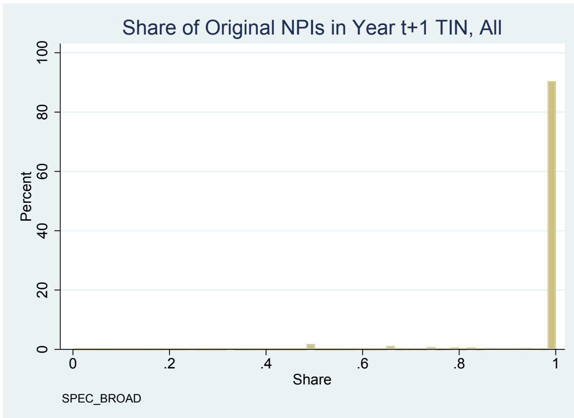
Figure 4: Year-to-year transition of TIN-Specialty Composition



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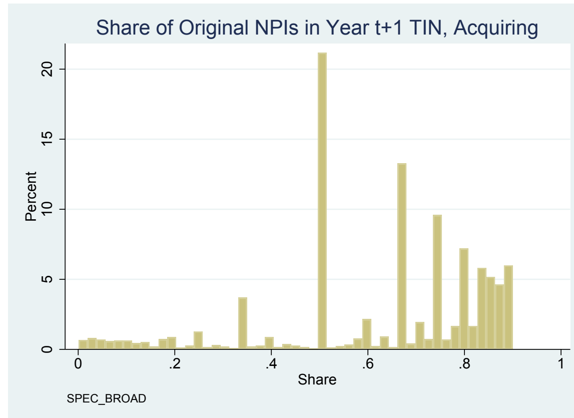
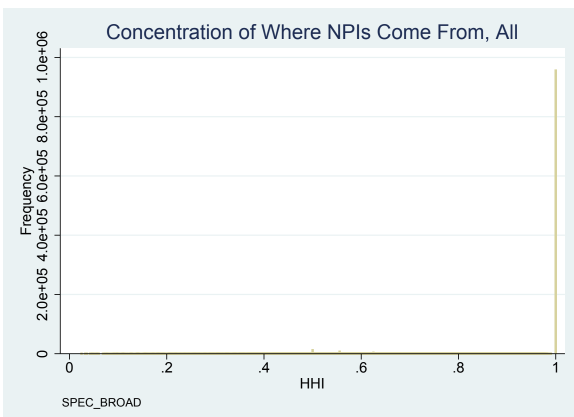


(b)

Figure 5: Concentration of year-to-year transition of TIN-Specialty Composition, by Outgoing (to) or Incoming (from) Baselines, Mergers



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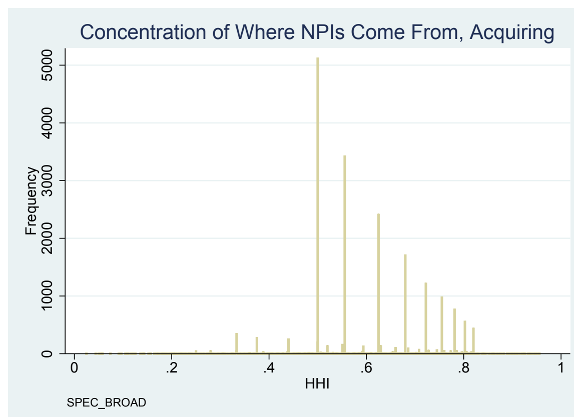

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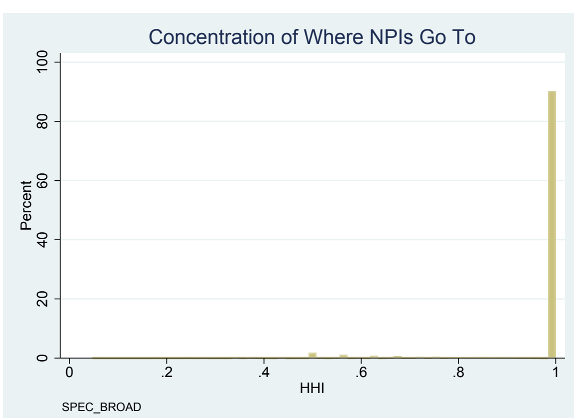

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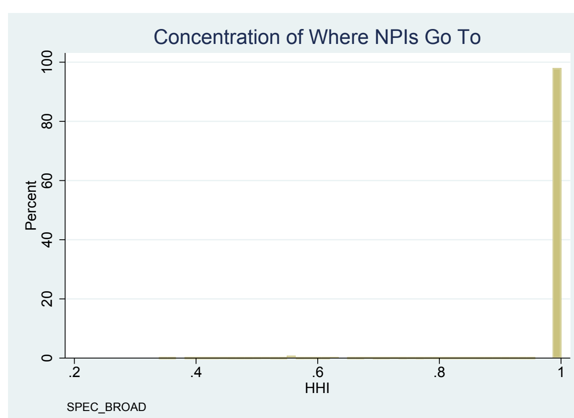
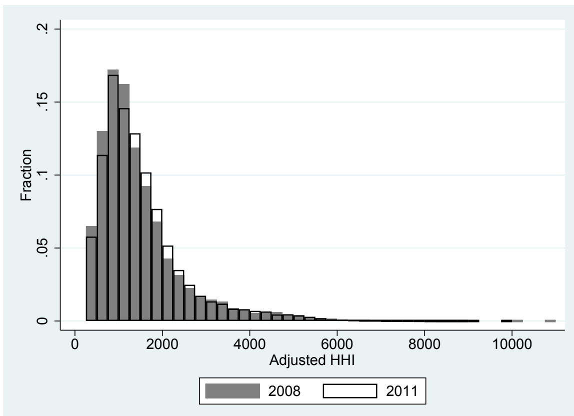
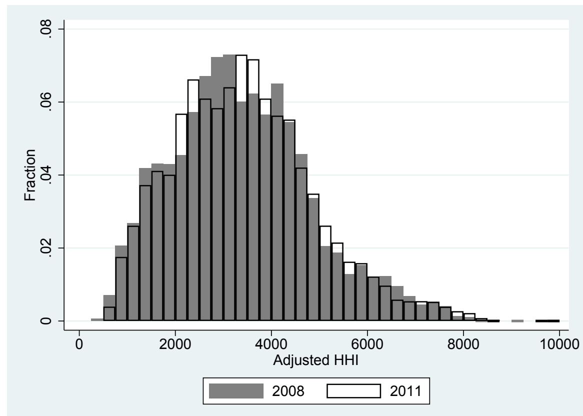


(d)

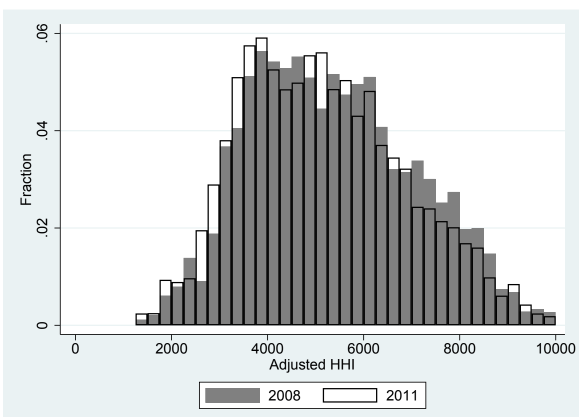
Figure 6: Patient-based measures of provider concentration, by selected specialty



(a) Primary Care



(b) Cardiology



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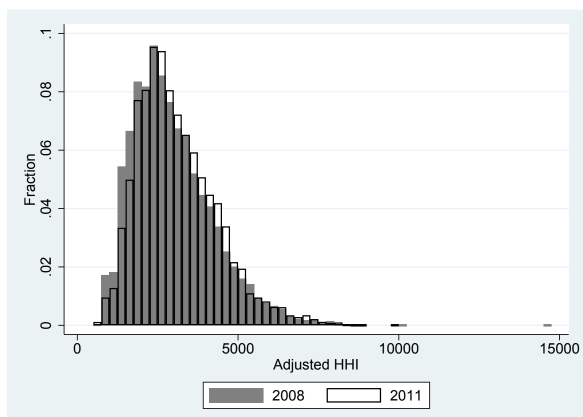
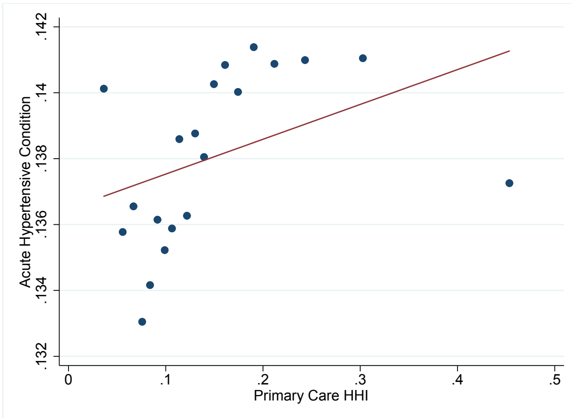


(d) Opthamology

Figure 7: Bin scatters of primary care concentration-health outcome relationships for hypertensives, by disease and inclusion of 3-digit fixed effects.



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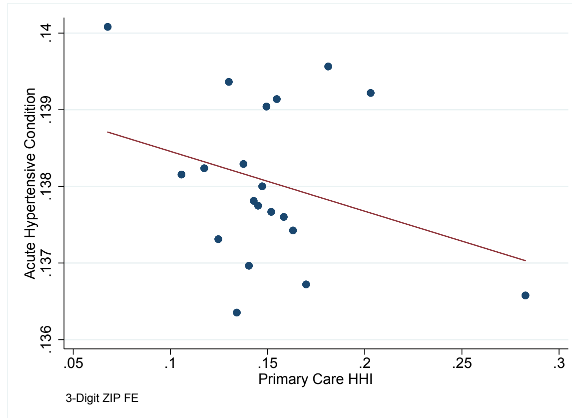

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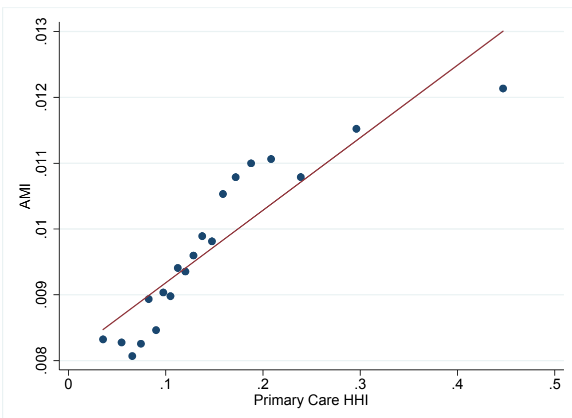

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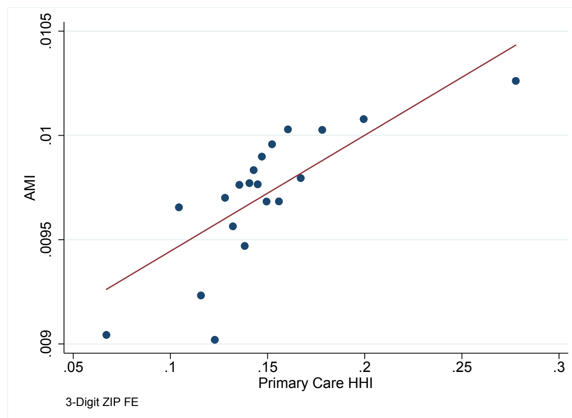

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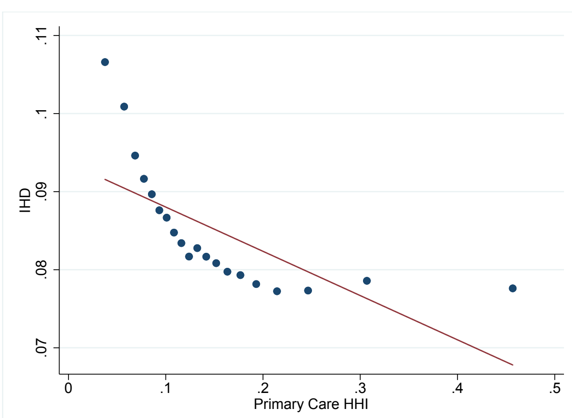

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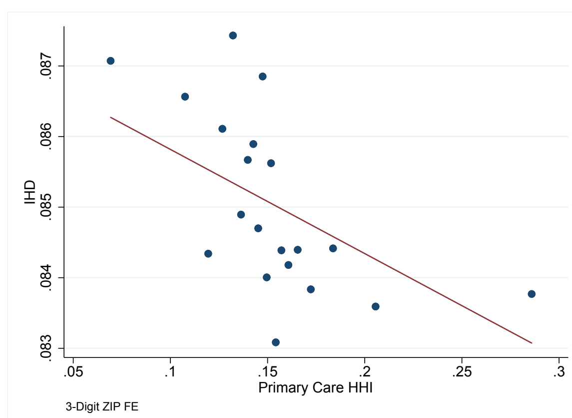

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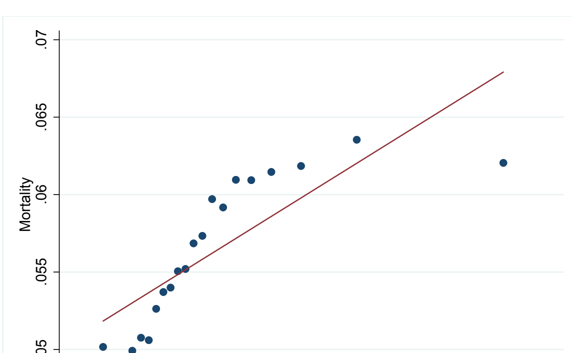


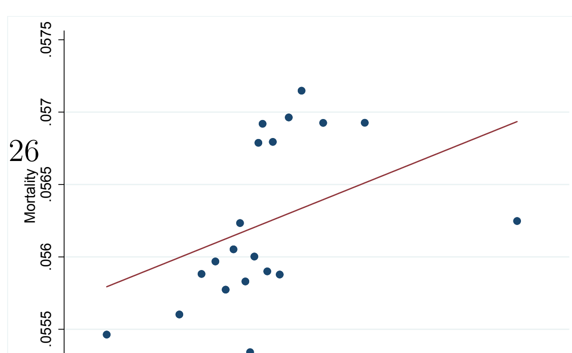
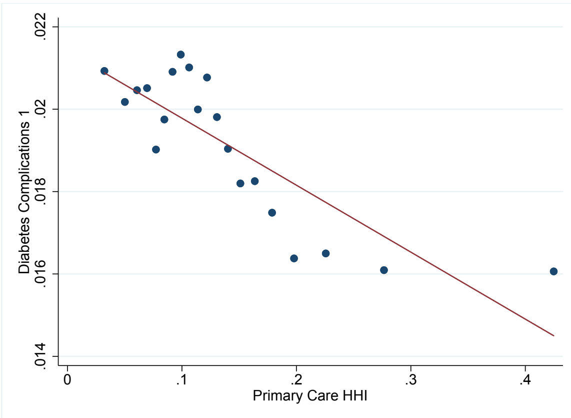


Figure 8: Bin scatters of primary care concentration-health outcome relationships for hypertensives, by disease and inclusion of 3-digit fixed effects.



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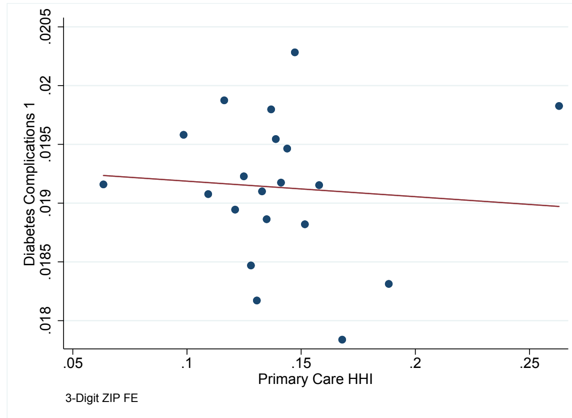

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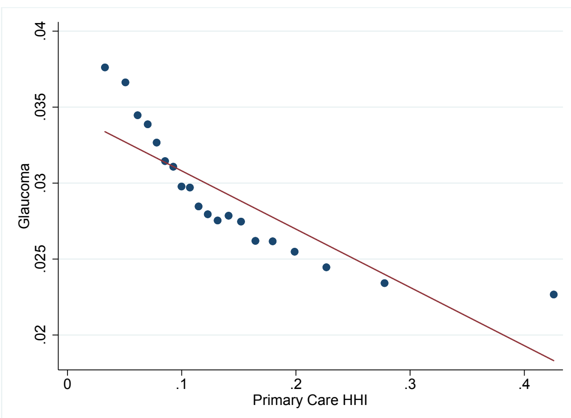

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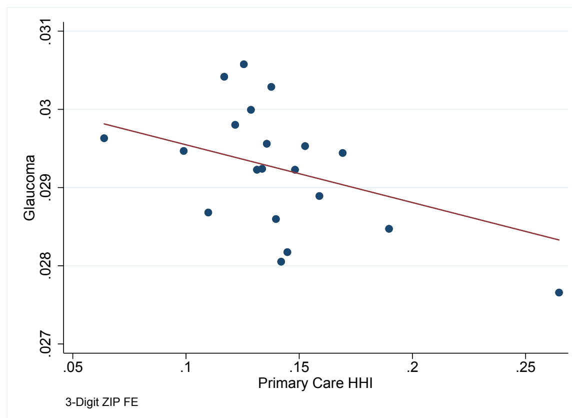

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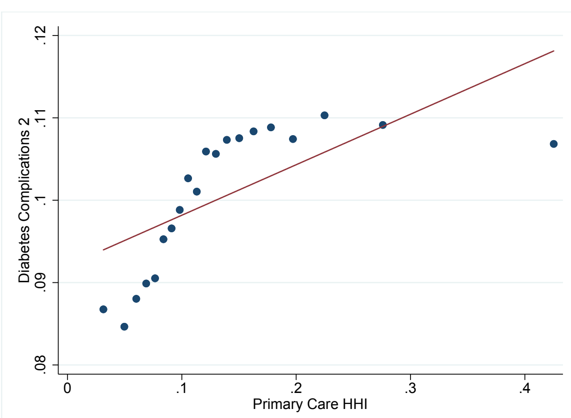

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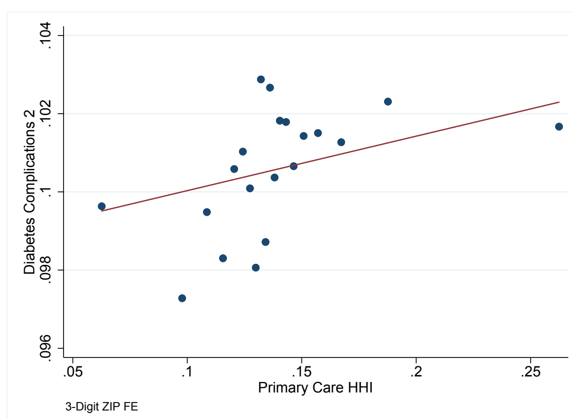

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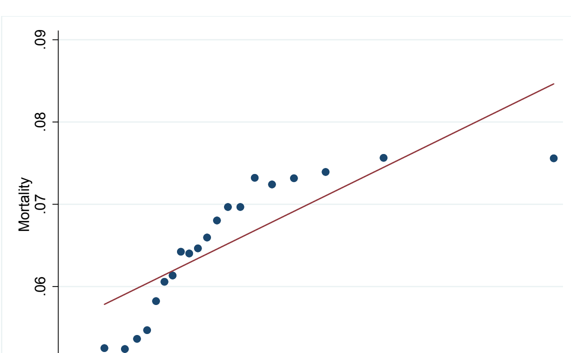


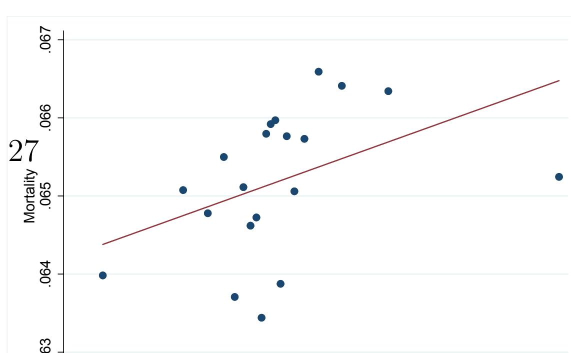
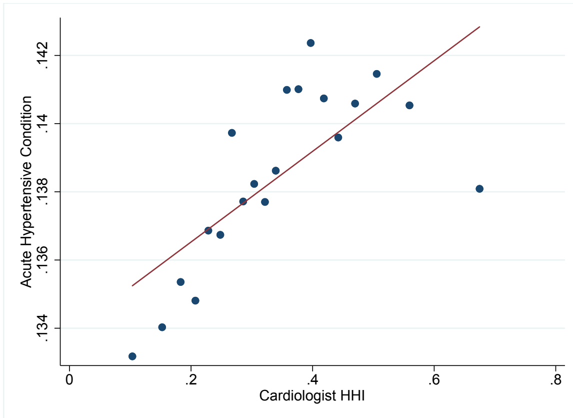


Figure 9: Bin scatters of cardiologist concentration-health outcome relationships for hypertensives, by disease and inclusion of 3-digit fixed effects.



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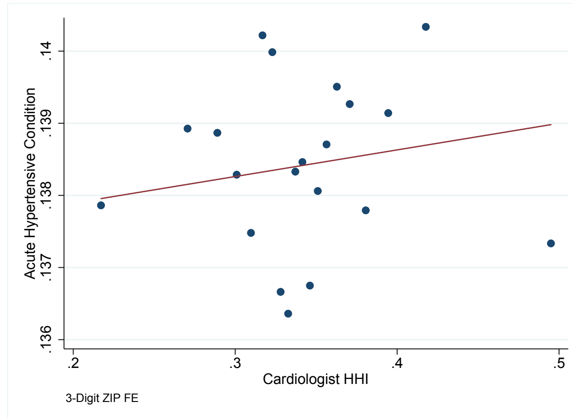

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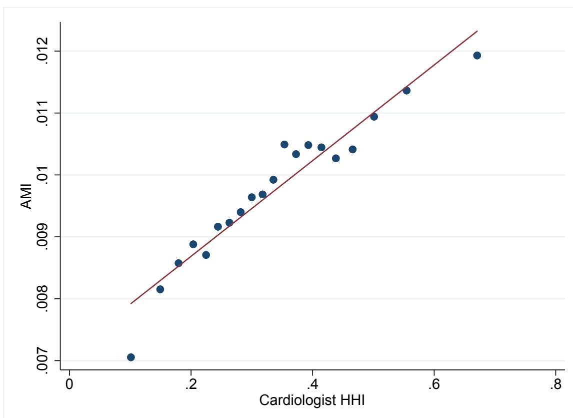

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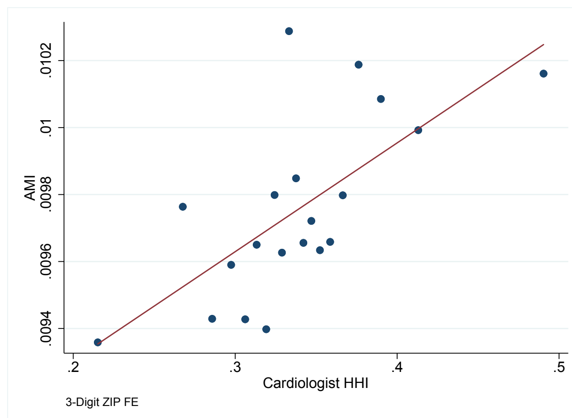

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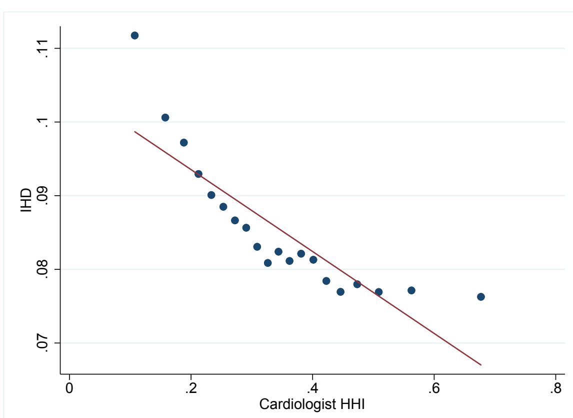

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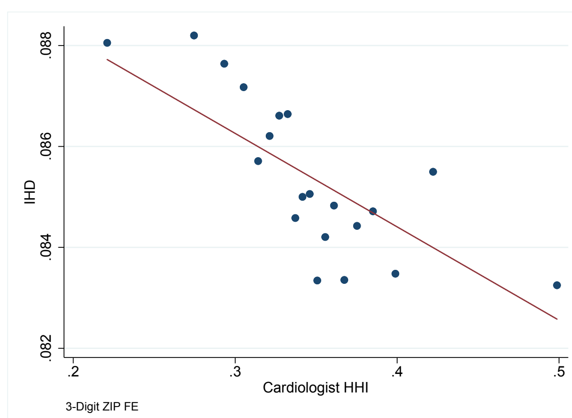

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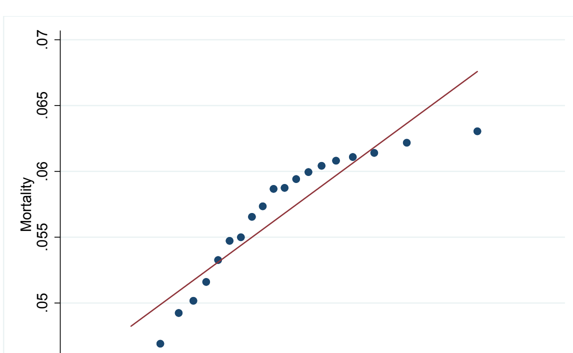

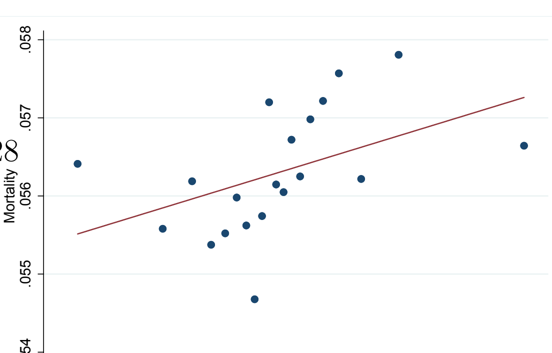

Table 1: Effect of Seeing a Provider Whose Practice Experienced a Merger or Acquisition

Merger Type	Diab. Comp 1	Glaucoma	Diab. Comp. 2	Death	Hyper. Compl.	AMI	IHD	Death	Death
				Saw Doctor in Leaving Group					
PC	0.00460**	-0.00180	-0.00414	-0.00153	0.00680**	0.000502	0.00276	0.00261	0.00926***
	(0.00193)	(0.00221)	(0.00437)	(0.00283)	(0.00283)	(0.000338)	(0.00226)	(0.00182)	(0.00103)
Specialist	0.00480	-0.00124	0.00395	-0.000631	0.0266***	0.00160**	0.0540***	-0.00142	0.0157***
	(0.00334)	(0.00279)	(0.00582)	(0.00362)	(0.00519)	(0.000752)	(0.00706)	(0.00256)	(0.00139)
PC-to-Sp	-0.00193	-0.00205	-0.0163*	0.000689	-0.00646	-0.000580	0.00477	-0.00525	-0.00477***
	(0.00366)	(0.00424)	(0.00938)	(0.00530)	(0.00689)	(0.000803)	(0.00554)	(0.00323)	(0.00127)
Sp-to-PC	-0.00614*	-0.00829	0.000543	0.00825	-0.00424	0.00201	0.0169	0.00828*	0.00135
	(0.00367)	(0.00554)	(0.0106)	(0.00681)	(0.00976)	(0.00152)	(0.0135)	(0.00486)	(0.00160)
Constant	-0.00509***	0.0119***	-0.0320***	-0.0282***	0.00803***	0.000269	0.00379	-0.0309***	-0.0247***
	(0.00180)	(0.00301)	(0.00467)	(0.00263)	(0.00252)	(0.000243)	(0.00234)	(0.00162)	(0.000965)
N	250,250	229,441	206,425	261,021	503,503	629,570	442,942	633,760	4,942,334
R-squared	0.011	0.077	0.043	0.106	0.048	0.006	0.036	0.102	0.103
Sample Mean	0.012	0.025	0.066	0.035	0.061	0.001	0.039	0.033	0.051
Condition	Diabetics	Diabetics	Diabetics	Diabetics	Hypert	Hypert	Hypert	Hypert	All
Gender	All	All	All	All	All	All	All	All	All

Notes: Estimates for OLS models, with standard errors clustered by three-digit ZIP code. Each column reports the effect of mergers by merger types: horizontal between primary care (PC), horizontal between medical specialists (Specialist), vertical with a PC joining a medical specialists (PC-to-Specialist) and a specialist joining a PC (Specialist-to-PC). The first panel reports the estimates for patients who saw a doctor in a group which lost providers. The second panel reports the estimates for patients who saw a doctor in a group which gained providers and could be characterized . All specifications include indicators for age-by-gender, race, relevant co-morbidities, and three-digit ZIP code fixed effects. We also include controls if the patient saw a doctor in a group that experience gains or losses that correspond to horizontal and cross-specialty vertical mergers for other specialties.

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 2: Effect of Seeing a Provider Whose Practice Experienced a Merger or Acquisition

	Saw Doctor in Absorbing Group								
Merger Type	Diab. Comp 1	Glaucoma	Diab. Comp. 2	Death	Hyper. Compl.	AMI	IHD	Death	Death
PC	0.00205***	-0.00114	0.00262	0.00650***	0.0152***	0.00179***	0.00698***	0.00452***	0.00495***
	(0.000778)	(0.000933)	(0.00189)	(0.00119)	(0.00151)	(0.000309)	(0.00129)	(0.000859)	(0.000720)
Specialist	0.00236***	-0.00118	0.00552***	0.00253**	0.0348***	0.00448***	0.0518***	0.00258***	0.00247***
	(0.000764)	(0.000905)	(0.00185)	(0.00116)	(0.00202)	(0.000351)	(0.00269)	(0.000969)	(0.000822)
PC-to-Sp	-0.00266***	-0.00112	-0.00215	-0.00465***	-0.0108***	-0.000459	-0.00615***	-0.00443***	-0.00280***
	(0.000724)	(0.000826)	(0.00177)	(0.00125)	(0.00154)	(0.000319)	(0.00126)	(0.000898)	(0.000727)
Sp-to-PC	-0.000108	-0.000398	0.0120***	0.00720***	0.0104***	0.00177***	0.0142***	0.00583***	0.00806***
	(0.000888)	(0.00104)	(0.00209)	(0.00154)	(0.00238)	(0.000460)	(0.00295)	(0.00114)	(0.000970)
Constant	-0.0109***	0.0146***	-0.0505***	-0.0188***	-0.0431***	-0.00413***	-0.0313***	-0.0216***	-0.0374***
	(0.00137)	(0.00210)	(0.00394)	(0.00189)	(0.00201)	(0.000378)	(0.00222)	(0.00117)	(0.000978)
N	1,029,403	917,321	794,843	1,077,408	1,943,317	2,616,877	1,702,534	2,645,503	4,942,334
R-squared	0.011	0.060	0.049	0.111	0.102	0.017	0.073	0.106	0.108
Sample Mean	0.017	0.031	0.093	0.051	0.113	0.006	0.071	0.044	0.051
Condition	Diabetics	Diabetics	Diabetics	Diabetics	Hypert	Hypert	Hypert	Hypert	All
Gender	All	All	All	All	All	All	All	All	All

Notes: Estimates for OLS models, with standard errors clustered by three-digit ZIP code. Each column reports the effect of mergers by merger types: horizontal between primary care (PC), horizontal between medical specialists (Specialist), vertical with a PC joining a medical specialists (PC-to-Specialist) and a specialist joining a PC (Specialist-to-PC). The first panel reports the estimates for patients who saw a doctor in a group which lost providers. The second panel reports the estimates for patients who saw a doctor in a group which gained providers and could be characterized . All specifications include indicators for age-by-gender, race, relevant co-morbidities, and three-digit ZIP code fixed effects. We also include controls if the patient saw a doctor in a group that experience gains or losses that correspond to horizontal and cross-specialty vertical mergers for other specialties.
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 3: Effect of Seeing a Provider Whose Practice Absorbed Other Providers, Separately by Primary Care Concentration

Merger Type	Hyper. Compl.	Hyper. Compl.	Hyper. Compl.	Hyper. Compl.	Hyper. Compl.
PC	0.0152***	0.0248***	0.0131***	0.0118***	0.00937***
	(0.00151)	(0.00299)	(0.00270)	(0.00278)	(0.00301)
Specialist Merger	0.0348***	0.0398***	0.0347***	0.0302***	0.0205***
	(0.00202)	(0.00321)	(0.00317)	(0.00370)	(0.00473)
PC-to-Specialist	-0.0108***	-0.0213***	-0.0102***	-0.00831***	-0.00544**
	(0.00154)	(0.00372)	(0.00277)	(0.00280)	(0.00251)
Specialist-to-PC	0.0104***	0.00797*	0.00690*	0.0130***	0.0152***
	(0.00238)	(0.00481)	(0.00374)	(0.00371)	(0.00414)
Constant	-0.0431***	-0.0408***	-0.0387***	-0.0397***	-0.0482***
	(0.00201)	(0.00358)	(0.00342)	(0.00399)	(0.00486)
Observations	1,943,317	497,836	484,316	467,996	492,551
R-squared	0.102	0.102	0.102	0.102	0.107
Sample Mean	0.113	0.125	0.112	0.107	0.108
Condition	Hypertension	Hypertension	Hypertension	Hypertension	Hypertension
Gender	All	All	All	All	All
HHI Bin		.0245911-	.0854763-	.1243352-	.1820587-
HHI Type		PC	PC	PC	PC
Merger Type	AMI	AMI	AMI	AMI	AMI
PC	0.00179***	0.00182***	0.00194***	0.00127**	0.00223***
	(0.000309)	(0.000569)	(0.000543)	(0.000565)	(0.000692)
Specialist Merger	0.00448***	0.00496***	0.00383***	0.00417***	0.00550***
	(0.000351)	(0.000550)	(0.000625)	(0.000730)	(0.00109)
PC-to-Specialist	-0.000459	-0.00102	0.000798	-0.000804	-0.000579
	(0.000319)	(0.000642)	(0.000630)	(0.000580)	(0.000589)
Specialist-to-PC	0.00177***	0.00100	0.00223***	0.00266***	0.000962
	(0.000460)	(0.000935)	(0.000768)	(0.000768)	(0.000985)
Constant	-0.00413***	-0.00279***	-0.00457***	-0.00370***	-0.00610***
	(0.000378)	(0.000582)	(0.000704)	(0.000833)	(0.00109)
Observations	2,616,877	693,862	651,757	623,117	647,403
R-squared	0.017	0.017	0.017	0.018	0.020
Sample Mean	0.006	0.006	0.006	0.006	0.007
Condition	Hypertension	Hypertension	Hypertension	Hypertension	Hypertension
Gender	All	All	All	All	All
HHI Bin		.0245911-	.0854763-	.1243352-	.1820587-
HHI Type		PC	PC	PC	PC

Merger Type	IHD	IHD	IHD	IHD	IHD
PC	0.00698***	0.00853***	0.0114***	0.00515**	0.000906
	(0.00129)	(0.00253)	(0.00236)	(0.00227)	(0.00231)
Specialist Merger	0.0518***	0.0536***	0.0499***	0.0456***	0.0450***
	(0.00269)	(0.00384)	(0.00474)	(0.00442)	(0.00527)
PC-to-Specialist	-0.00615***	-0.0118***	-0.00508**	-0.00463**	-0.00435**
	(0.00126)	(0.00331)	(0.00243)	(0.00215)	(0.00199)
Specialist-to-PC	0.0142***	0.0180***	0.00805*	0.0171***	0.0129***
	(0.00295)	(0.00604)	(0.00458)	(0.00462)	(0.00483)
Constant	-0.0313***	-0.0342***	-0.0263***	-0.0263***	-0.0303***
	(0.00222)	(0.00471)	(0.00320)	(0.00325)	(0.00364)
Observations	1,702,534	410,287	426,717	419,041	445,941
R-squared	0.073	0.081	0.071	0.071	0.071
Sample Mean	0.071	0.090	0.070	0.064	0.061
Condition	Hypertension	Hypertension	Hypertension	Hypertension	Hypertension
Gender	All	All	All	All	All
HHI Bin		.0245911-	.0854763-	.1243352-	.1820587-
HHI Type		PC	PC	PC	PC

Merger Type	Death	Death	Death	Death	Death
PC	0.00452***	0.00508***	0.00349**	0.00578***	0.00483**
	(0.000859)	(0.00138)	(0.00158)	(0.00162)	(0.00209)
Specialist Merger	0.00258***	0.00740***	0.000242	0.00373**	-0.00379
	(0.000969)	(0.00156)	(0.00138)	(0.00181)	(0.00238)
PC-to-Specialist	-0.00443***	-0.00634***	-0.00509***	-0.00477***	-0.00141
	(0.000898)	(0.00199)	(0.00174)	(0.00155)	(0.00148)
Specialist-to-PC	0.00583***	0.00409	0.00310**	0.00770***	0.0121***
	(0.00114)	(0.00252)	(0.00153)	(0.00176)	(0.00217)
Constant	-0.0216***	-0.0183***	-0.0223***	-0.0229***	-0.0235***
	(0.00117)	(0.00195)	(0.00210)	(0.00221)	(0.00253)
Observations	2,645,503	700,400	658,320	630,376	655,662
R-squared	0.106	0.105	0.108	0.109	0.108
Sample Mean	0.044	0.042	0.044	0.045	0.047
Condition	Hypertension	Hypertension	Hypertension	Hypertension	Hypertension
Gender	All	All	All	All	All
HHI Bin		.0245911-	.0854763-	.1243352-	.1820587-
HHI Type		PC	PC	PC	PC

Merger Type	Death	Death	Death	Death	Death
PC	0.00495***	0.00507***	0.00324**	0.00502***	0.00384**
	(0.000720)	(0.00130)	(0.00143)	(0.00151)	(0.00184)
Specialist Merger	0.00247***	0.00671***	0.000304	0.00297*	-0.00447**
	(0.000822)	(0.00147)	(0.00129)	(0.00164)	(0.00212)
PC-to-Specialist	-0.00280***	-0.00676***	-0.00515***	-0.00471***	-0.00199
	(0.000727)	(0.00191)	(0.00164)	(0.00139)	(0.00136)
Specialist-to-PC	0.00806***	0.00406*	0.00311**	0.00699***	0.0117***
	(0.000970)	(0.00238)	(0.00144)	(0.00162)	(0.00202)
Constant	-0.0374***	-0.0325***	-0.0327***	-0.0345***	-0.0345***
	(0.000978)	(0.00171)	(0.00171)	(0.00171)	(0.00183)
Observations	4,942,334	822,379	789,250	762,036	807,047
R-squared	0.108	0.103	0.106	0.107	0.107
Sample Mean		0.038	0.039578	0.040776	0.042709
Condition	All	All	All	All	All
Gender	All	All	All	All	All
HHI Bin		.0245911-	.0854765-	.1243452-	.18206-
HHI Type		PC	PC	PC	PC

Notes: Estimates for OLS models, with standard errors clustered by three-digit ZIP code. Each column reports the effect of mergers by merger types: horizontal between primary care (PC), horizontal between medical specialists (Specialist), vertical with a PC joining a medical specialists (PC-to-Specialist) and a specialist joining a PC (Specialist-to-PC). Each panel corresponds to a different medical outcome among hyptertensives. Each column corresponds to separately estimating the specifications by the primary care concentration level faced by the beneficiary. The thresholds for the primary care concentration level bins were constructed to create approximately equally-sized bins. All specifications include indicators for age-by-gender, race, relevant co-morbidities, and three-digit ZIP code fixed effects. We also include controls if the patient saw a doctor in a group that experience gains or losses that correspond to horizontal and cross-specialty vertical mergers for other specialties.
* significant at 10%; ** significant at 5%; *** significant at 1%