# PHYSICIAN MARKET CONCENTRATION AND PATIENT WELFARE: AN EXAMINATION OF MEDICARE BENEFICIARIES

Thomas Koch

Brett Wendling

Nathan E. Wilson[1]

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**ABSTRACT**

We consider the effects that local cardiology market structure has on utilization and health outcomes for four patient populations with specific cardiac conditions. We find that an increase in concentration leads to statistically and economically significant increases in the likelihood of negative health outcomes. For example, we find that moving from a zip-code around the 25th percentile of cardiology market concentration during our sample to one around the 75th percentile would be associated with around 0.2-0.3 percentage point increase in risk-adjusted mortality in three of our patient populations. We also find that patients in more concentrated markets utilized more health care. For example, moving from a zip-code at the 25th percentile of cardiology market concentration to one at the 75th would be associated with an 18% to 31% increase in total expenditures. Overall, our analysis implies an increase in cardiology market concentration is associated with worse outcomes for patients without offsetting clinical efficiencies.

***Key words***. Competition, Industrial Organization, Physicians, Medicare, Cardiology

***JEL Codes.*** I11, L10, L40

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[1] Bureau of Economics, Federal Trade Commission. The views expressed in this article are those of the authors. They do not necessarily represent those of the Federal Trade Commission or any of its Commissioners. E-mail: tkoch@ftc.gov, bwendling@ftc.gov, nwilson@ftc.gov. We are grateful for feedback from Abe Dunn, Daria Pelech, Laurence Baker, and commenters at the 2016 ASHEcon Conference in Philadelphia.

## I. INTRODUCTION

Physicians increasingly work in large practices rather than small groups or as solo practitioners.[2] In part because it has been correlated with an uptick in mergers and acquisitions, this change has coincided with rising concern about the level of competition in physician markets (Dunn & Shapiro, 2014; Baker L. , Bundorf, Royalty, & Levin, 2014; Kleiner, White, & Lyons, 2015).[3] An emerging empirical literature supports such concern, for scholars have found evidence that more concentrated (i.e., less competitive) physician markets have higher commercial insurance reimbursement rates (Dunn & Shapiro, 2014; Baker L. , Bundorf, Royalty, & Levin, 2014; Schneider, Li, Klepser, Peterson, Brown, & Scheffler, 2008; Sun & Baker, 2015).

In this paper, we extend the literature on physician market concentration by considering its relationship to clinical quality and health services utilization.[4] To do this, our analysis leverages rich data on Medicare fee-for-service beneficiaries. We focus on patients with heart-related problems as the prior literature has suggested that cardiology markets have become especially concentrated (Baker L. , Bundorf, Royalty, & Levin, 2014; Dunn & Shapiro, 2016), at least partially as a result of hospitals acquiring cardiology groups (Koch, Wendling, & Wilson,

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[2] A recent survey by the American Medical Association (AMA) found that the percentage of physicians in solo practice declined by 25 percentage points (from 44% to 19%) between 1983 and 2014. Simultaneously, the share of physicians in practices with 25 or more doctors increased fourfold (from 5% to 20%) (Kane, 2015).

[3] For discussion of physician mergers, see discussion in both practitioner-oriented and scholarly journals (Townsend, 2013; Kleiner, White, & Lyons, 2015).

[4] Studies of hospital mergers and market concentration have often documented a negative link between competition and quality (Gaynor & Town, 2012; Vogt & Town, 2006). Similar connections have also been found in other healthcare markets (Wilson, 2016).

forthcoming; Song, Wallace, Neprash, McKellar, Chernew, & McWilliams, 2015).[5] Moreover, cardiac conditions affect many patients, and are associated with observable health events.

To test whether competition affects utilization and clinical quality, we identify several sets of patients exposed to cardiology markets by virtue of having been seen for a heart-related issue in the prior year. We assess different outcome variables' relationship to market concentration using an approach standard in the healthcare competition literature (Kessler & McClellan, 2000; Zwanziger, Melnick, & Mann, 1990) while controlling for variation in patient-level risk factors.

Our data support the prior literature's conclusion that cardiology markets have grown less competitive in recent years. Moreover, the results of our regression analyses suggest that differences in competition are associated with statistically and economically significant changes in patients' health outcomes. We find this consistently for outcomes ranging from mortality to increased visits to the emergency room (ER). For example, we find that moving from a zip-code around the 25$^{th}$ percentile of cardiology market concentration during our sample to one around the 75$^{th}$ percentile would be associated with around 0.3 percentage point increase in risk-adjusted mortality in the three of our sample populations. These effects are equivalent to close to a 5% increase in the risk of mortality relative to the sample population means. We find similar results for incidence of AMIs, needing to go to an emergency room (ER), and incidence of readmissions. The negative correlation between concentration and quality is consistent with economic theory's predictions about markets where compensation is administratively determined (Gaynor, 2006).

In addition to finding evidence of lower clinical quality in more concentrated markets, our analyses show that overall expenditures on health services increase as competition declines. For example, moving from a zip-code at the 25$^{th}$ percentile of cardiology market concentration to one at the 75$^{th}$ would be associated with an 18% to 31% increase in total expenditures depending

[5] In future work, we hope to extend our analytical approach to other specialties. The word "markets" here and elsewhere is used colloquially; no steps have been taken to test whether cardiology would constitute a properly defined antitrust market.

on sample population. This appears driven by higher hospital expenditures, which outweigh modest reductions in average spending on physician services. Since the higher total expenditures are not associated with improvements in health outcomes, our results indicate that reductions in competition lead to a deterioration in the value of healthcare service provision.

Overall, our results complement those of other ongoing research on physician markets. In particular, Dunn and Shapiro (2016) find that cardiologists in more concentrated markets perform more services on commercially insured patients than do otherwise similar ones in less concentrated markets. Moreover, insofar as we find that concentration increases expenditures in hospitals – but not payments to physicians for services provided in office (as opposed to outpatient hospital) settings – we believe our results connect to the literature focusing on the financial (Koch, Wendling, & Wilson, forthcoming; Capps, Dranove, & Ody, 2016; Baker, Bundorf, & Kessler, 2014; Neprash, Chernew, Hicks, Gibson, & McWilliams, 2015) and quality (Carlin, Dowd, & Feldman, 2015; Scott, Orav, Cutler, & Jha, forthcoming; Koch, Wendling, & Wilson, 2016) implications of vertical integration among health care providers.

## II. DATA & METHODS

### A. Study Population of Patients and Organizations

Our analysis relies on 2005-2012 claims and enrollment information for a 5% sample of fee-for-service Medicare beneficiaries. The 5% sample of Medicare beneficiaries leads to approximately 2.5 million persons per year. The claims data are inclusive of inpatient admissions, hospital outpatient visits, and office-based visits. The data contain rich details about the procedures performed (e.g., CPT codes for outpatient visits), patients' ailments (e.g., ICD-9 diagnosis codes), and the specific dates on which each "event" occurred.

Using the claims and enrollment information, we narrow attention to four overlapping samples of patients likely to be affected by differences in cardiology markets.[6] In all cases, we identify patients by looking at their treatment history in the prior year. First, we identify patients

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[6] Detailed information on the construction of the dataset used in the analysis can be found in the Appendix.

who suffer from hypertension. Second, we focus on the smaller set of patients who suffer from a cardiac condition. Third, we focus on patients suffering from an acute cardiac condition. Fourth, we identify patients who suffered an AMI.

In the claims data, attending doctors are identified by a unique identifier (either NPI or UPIN). Financial linkages across physicians are established using the clinicians' tax identification numbers (TIN).[7]

### B. Study Variables

#### *i. Outcomes*

We focus on two groups of outcome variables. First, we consider metrics related to the quality of care: mortality, the incidence of AMIs, an indicator for whether a patient visited an emergency room (outpatient or inpatient), and whether or not a patient had to be readmitted. Second, we consider several different proxies for the utilization of health care services. We do this by looking at total expenditures, expenditures going to hospitals, expenditures to physicians (which would include a de facto facility component for visits taking place in doctors' offices), and the number of days a patient spent in a hospital.

Finding that an increase in concentration is associated with either deterioration in the quality metrics (without decreased utilization) or an increase in utilization (without any compensating improvement in quality) would be evidence that competition incentivizes higher value clinical services. A finding that higher concentration is associated with higher spending but lower incidence of adverse health outcomes has less obvious welfare implications. It could indicate that competition results in a race to the bottom that prevents clinicians from spending enough time with patients to effectively help them avoid bad outcomes. Alternatively, it could indicate that with market power, clinicians over-provide clinical quality relative to what a social planner would choose (Gaynor, 2006).

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[7] Using TINs is common in the literature (Baker L. , Bundorf, Royalty, & Levin, 2014). Further details on the construction of our analytical samples can be found in the Online Data Appendix.

*ii. Measure of Concentration*

Our independent variable of interest is the competitiveness of patients' local physician market. We measure this using an approach similar to ones in the prior research (Zwanziger, Melnick, & Mann, 1990; Kessler & McClellan, 2000; Dunn & Shapiro, 2014). Our measure differs from past methods because we do not observe provider location, making it impossible to estimate patient choice models that heavily rely on distance. Instead, we use observed shares within narrow geographic regions for a comparatively homogeneous population.[8]

We begin by identifying all outpatient claims for services delivered by cardiologists. For each observation, we observe the TIN of the provider associated with the claim. With this information, we construct annual measures at the patient zip-code-level of the Herfindahl-Hirschman Index (HHI) using market shares based on the allowed amount of spending.[9] The HHI is a standard metric used in industrial organization and antitrust to assess the level of competitiveness in markets. It is defined as the sum of squared market shares multiplied by 10,000.[10]

As discussed in Kessler and McClellan (2000), the zip-code-level HHIs may not be good predictors of the impact of competition; they would imply that physicians differentiate their behavior based on the residences of patients. To correct for this problem, we follow Kessler and McClellan (2000) in constructing adjusted measures that assume physicians' quality choices

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[8] To the extent that location is endogenous, we believe the selection process would tend to produce attenuated estimates of the relationship between concentration and economic outcomes. Thus, our estimates are conservative.

[9] The HHIs calculated here are not for market areas as spelled out in the *Horizontal Merger Guidelines* (U.S. Department of Justice and the Federal Trade Commission, 2010), so the competitive implications of various concentration levels may not correspond to those suggested by the *Guidelines*. As discussed in the Online Data Appendix, there are advantages and disadvantages to constructing the HHIs with different measures. We believe that allowed amounts make the most sense as they implicitly account for differential incentives that vertically integrated organizations may have.

[10] The HHI is not a perfect measure of competition. However, it is a standard proxy for the level of competition in a market, and a large number of papers have demonstrated its value as a proxy in health care markets (Gaynor & Town, 2012).

reflect a weighted average of the competitiveness of the different markets their patients come from. The average effect of competition for patients from a given zip-code can then be assessed by taking the weighted average of the providers chosen by patients living in that zip-code.

Across zip-codes, our adjusted zip-code concentration measure varies depending on the number and relative desirability of different cardiology practices. Within zip-codes, the concentration measure will change over time for three reasons. First, entry, exit, or mergers of cardiology practices will cause the adjusted HHIs to change. Second, concentration will be impacted by differences over time in the relative preference of individuals for different practice characteristics.[11] Third, the concentration of a given zip-code will shift as the populations of nearby zip-codes change, all else equal.

Using one observation for each zip-code-year and weighting by the number of beneficiaries, we find large cross-sectional differences in the level of concentration.[12] This can be seen in Figure 1. For example, an observation at the 25$^{th}$ percentile of concentration has an adjusted HHI of 2,306 while a zip-code at the 75$^{th}$ percentile has an adjusted HHI of 3,958.

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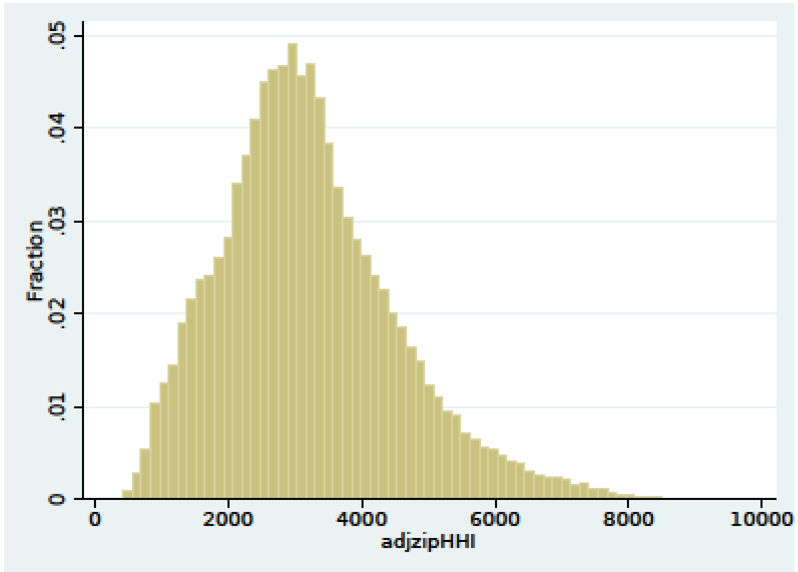
[11] This is because the initial zip-level HHIs imply that within a zip-code all beneficiaries have the same preferences for providers. It is as though we are estimating a semi-parametric choice model wherein which the only binning variable is patient zip-code. An alternative would be to consider adding additional binning variables when constructing the weighted concentration measures (Gowrisankaran & Town, 2003). However, given that our sample is made up of Medicare beneficiaries of broadly similar age, we believe our simpler approach is valid. To the extent that we misestimate our concentration measure, the recovered estimates will be attenuated towards zero. Therefore, the findings should be considered conservative evidence of the impact of concentration.

[12] The extent of the variation can be seen in Figure 2 in the Online Appendix.

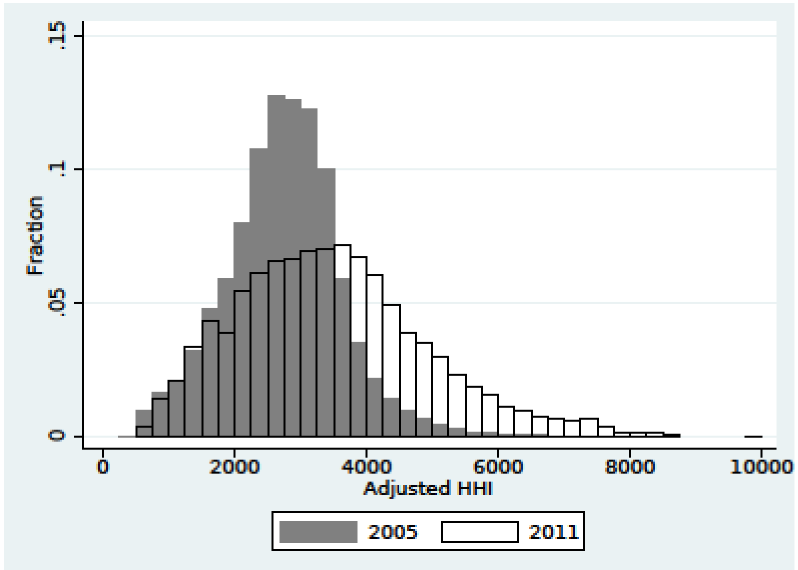
**Figure 1: Histogram of Concentration at the Year-Zip-code Level**




We also find that there is substantial variation in concentration within zip-codes over time. For example, we find that the standard deviation of concentration within more than half of all zip-codes is at least 13% of the mean level of that zip-code's concentration over the seven-year sample.[13] Moreover, we find that much of the variation in concentration over time reflects the fact that many markets were growing more concentrated. In particular, the average patient's zip-code had an adjusted HHI of 2,752 in 2005 as compared to 3,365 in 2011. Further evidence of the trend towards greater concentration can be seen by comparing the distributions of concentration from the beginning to the end of our sample period as in Figure 2. The darker histogram shows the distribution of zip-code level adjusted HHIs for 2005, while the unshaded histogram shows the same distribution in 2011. The Figure shows that the distribution of concentration shifted to the right from the beginning to the end of our sample period, and there is a much larger tail of highly concentrated markets in the latter period.

[13] This can be seen in Figure 3 in the Online Appendix, which shows the distribution of the coefficients of variation for concentration evaluated within zip-codes.

**Figure 2: Histograms of Zip-code Concentration over Time**




*iii. Risk-Adjusting Covariates*

We account for factors other than concentration that are likely to influence health outcomes and utilization by including a set of patient characteristic variables. Our demographic variables include five-year age categories (i.e., 60-64, 65-69, etc.), gender, and race (white, African American, and other). We also include comorbidity indicators for whether the beneficiary suffers from ESRD or diabetes. To account for unobserved differences in factors like income, wealth, and environmental quality, we use zip-code fixed effects. To address the possibility of systematic intertemporal variation, we include a set of year indicator variables.

## C. Statistical Analysis

In our econometric analyses, the unit of observation is the beneficiary-year. Across all of our outcome variables, our specifications take the same general form:

$$y_{imt} = \alpha \ln(\text{ADJZIPHHI})_{mt-1} + X_{it}\beta + Z_{it-1}\gamma + \delta_t + \eta_m + \varepsilon_{imt} \ ,$$

where $y_{imt}$ is the outcome of interest for beneficiary $i$ living in zip-code market $m$ in year, ADJZIPHHI$_{mt-1}$ is the level of concentration in $m$ in the prior year, $X_{it}$ are contemporary sociodemographic variables of the beneficiary, $Z_{it-1}$ are indicator variables for whether or not the beneficiary was diagnosed with a serious comorbidity in the previous year, $\delta_t$ are time fixed effects, $\eta_m$ are zip-code fixed effects, and $\varepsilon_{imt}$ is the idiosyncratic error.[14]

Because we include zip-code fixed effects in all models, the effect of competition is identified by variation in our concentration measure within zip-codes over time. We estimate the specifications using ordinary least squares (OLS), making those regressions with binary outcomes linear probability models. We cluster our standard errors at the zip-code level.

## III. Results

### A. Characteristics of the Samples

**Table 1: Summary Statistics**

| | Hyper | | Chronic | | Acute | | AMI | |
|---|---|---|---|---|---|---|---|---|
| | mean | sd | mean | sd | mean | sd | mean | sd |
| **Age** | 77.34 | 8.06 | 77.84 | 7.71 | 77.72 | 7.96 | 79.08 | 8.39 |
| **Female** | 0.64 | 0.48 | 0.66 | 0.47 | 0.66 | 0.47 | 0.55 | 0.50 |
| **ESRD t-1** | 0.01 | 0.09 | 0.01 | 0.08 | 0.01 | 0.09 | 0.04 | 0.19 |
| **Diabetes t-1** | 0.42 | 0.49 | 0.38 | 0.48 | 0.39 | 0.49 | 0.55 | 0.50 |
| **ADJHHI t-1** | 0.32 | 0.13 | 0.32 | 0.13 | 0.32 | 0.13 | 0.32 | 0.13 |
| **Died** | 0.06 | 0.24 | 0.05 | 0.21 | 0.05 | 0.22 | 0.17 | 0.37 |
| **AMI** | 0.01 | 0.11 | 0.01 | 0.10 | 0.01 | 0.10 | 0.07 | 0.26 |
| **Readmissions** | 0.07 | 0.40 | 0.06 | 0.36 | 0.07 | 0.38 | 0.25 | 0.81 |
| **1(ER)** | 0.34 | 0.47 | 0.32 | 0.47 | 0.34 | 0.47 | 0.57 | 0.50 |
| **Hospital Expenditures** | 6261 | 15818 | 5653 | 14568 | 6096 | 15355 | 14535 | 26130 |
| **Physician Expenditures** | 599.29 | 587.27 | 638.09 | 599.22 | 663.30 | 624.26 | 683.32 | 660.25 |
| **Total Expenditures** | 6860 | 15937 | 6291 | 14697 | 6759 | 15483 | 15218 | 26232 |
| **Days in Hospital** | 2.46 | 7.96 | 2.10 | 7.18 | 2.30 | 7.59 | 6.16 | 12.90 |
| **Observations** | 7478233 | | 4592453 | | 4262415 | | 78742 | |

[14] In our analyses, we assume beneficiaries' outcomes in year *t* will be affected by the adjusted HHI of their zip-code in year *t-1*. This will reduce the possibility of simultaneity bias.

Table 1 shows summary statistics for the different samples and variables used in the paper. The summary statistics show that a high proportion of our sample is female and many suffer from diabetes. The sample population's consumption of health care services is weighted towards those provided in hospital-based settings as the combined Medicare and beneficiary expenditures for hospital-based treatments are approximately four times those spent on physician services.

### B. Clinical Outcomes Analysis

**Table 2: Effects of Concentration on Clinical Outcomes**

| Sample | Died | AMI | 1(ER) | Log(Readmissions + 1) | N |
|---|---|---|---|---|---|
| **Hyper** | 0.012*** | 0.003*** | 0.033*** | 0.007*** | 7616752 |
| **Chronic** | 0.009*** | 0.002** | 0.028*** | 0.004** | 4651140 |
| **Acute** | 0.014*** | 0.001 | 0.033*** | 0.007*** | 4316207 |
| **AMI** | -0.007 | 0.033 | 0.104** | 0.013 | 79218 |

Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. * p<0.1; ** p<0.05; *** p<0.01.

Table 2 presents risk-adjusted effects of variation in cardiology market concentration on clinical outcomes for the four sample populations.[15] It consistently shows that an increase in market concentration correlates with a deterioration in patients' health outcomes. Out of 16 regressions, all but one show a positive correlation between concentration and the incidence of negative health outcomes. Moreover, these effects are precisely estimated. For the samples with large populations, only one regression out of 12 shows a relationship not statistically significant at the 1% level.

Not only is concentration consistently associated with bad health outcomes for patients, the magnitude of the connection is of economic significance. For example, the estimated coefficients imply that a hypertensive patient moving from a zip-code at the 25$^{th}$ percentile of concentration to one at the 75$^{th}$ percentile would be expected to have around a 0.3 percentage

[15] Complete output tables for the regressions summarized in Tables 2-3 are provided in the Online Appendix. See, specifically, Table 8 through Table 11.

point higher incidence of mortality. This is equivalent to an approximate 5% increase in risk relative to the population means. The effects are broadly similar for the other quality metrics and populations.

### C. Utilization Analysis

**Table 3: Effects of Concentration on Expenditures and Utilization**

| Sample | Log(Total Expenditures+1) | Log(Hosp Expenditures+1) | Log(Phys Expenditures+1) | Log(Hosp Days+1) | N |
|---|---|---|---|---|---|
| **Hyper** | 0.344*** | 0.629*** | -0.011 | 0.043*** | 7616752 |
| **Chronic** | 0.250*** | 0.597*** | -0.064*** | 0.032*** | 4651140 |
| **Acute** | 0.282*** | 0.625*** | -0.079*** | 0.052*** | 4316207 |
| **AMI** | 0.430** | 0.790*** | 0.245 | 0.178 | 79218 |

Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

Table 3 presents risk-adjusted effects of variation in cardiology market concentration on health care services utilization for the different sample populations. Similar to those shown in Table 2, the utilization results show that concentration is associated with economically and statistically significant consequences. In only three out of 16 regressions is the relationship between concentration and utilization not statistically significant at the 1% level. However, in contrast to the consistent effects for hospital-based expenditures, the results show that concentration is associated with both increases and *decreases* in various utilization metrics.

Not only are the effects on utilization statistically significant, they are very large in economic magnitude. Depending on sample population, the estimated coefficients imply that a hypertensive patient moving from a zip-code at the 25$^{th}$ percentile of concentration to one at the 75$^{th}$ percentile would have 18% to 31% increase in total expenditures. These net increases are driven by increased charges from hospitals as for most populations, an increase in concentration is associated with modest decreases in spending to physician. Consistent with these findings, patients from all samples also spend more time hospitalized in more concentrated markets. The magnitude of the effects vary somewhat but imply that a doubling in concentration would lead to 3%-18% more days in the hospital depending on the sample.

### D. Robustness

We have found our baseline results to be quite robust. Table 4 and Table 5 in the Online Appendix show the results for robustness models wherein we allowed patients' demographic characteristics to have different effects by county of residence. This richer specification did not lead to qualitatively different results. Similarly, Table 6 and Table 7 show that our conclusions are robust to calculating concentration using shares based on clinical visits rather than allowed spending.[16]

## IV. Discussion

In this national study of the impact of cardiology practice competition, we document significant variation in local cardiology markets concentration. Furthermore, the data suggest a substantial increase in recent years for most markets. Our regression analyses suggest that this increase in concentration has had economically and statistically significant effects on utilization and patient outcomes.

We find that higher physician market concentration is associated with higher total expenditures and utilization. Moreover, our analyses show that the increased expenditures do *not* consistently result in improvements in clinical outcomes. Indeed, we find that increased concentration generally leads to worse health outcomes. While we are unable to say whether the increased expenditures may be associated with non-clinical factors that increase beneficiary utility, these patterns are inconsistent with arguments that increased provider scale benefits

[16] Although not shown, we also found our results to be robust to still other permutations of the data and identification. For example, we discretized our measure of concentration and generally found that the concentration variable's effect was concave but monotonic as implied by our preferred specification. In addition, we separately estimated our effects models for zip-codes at different levels of the population density distribution. Although there was some variation in the magnitude of the estimated effects, our baseline story broadly held across the different levels. Details are available from the authors upon request.

patients. This fits with other evidence on physician organizational changes (Burns, Goldsmith, & Sen, 2013).

One of the more interesting results from our analyses is that the increased expenditures from cardiology market concentration stem from services provided in hospitals. Spending on physician services is actually lower in more concentrated markets. This result could have several explanations. For example, it could reflect less incentive to provide quality office-based service leading to greater need for acute care services available only in hospitals. Alternatively, hospital acquisitions of physician practices could lead to higher physician concentration, and other research has shown such vertical integration to be correlated with increased hospital billing (see, e.g., Koch, Wendling & Wilson, 2015). We are optimistic that future research will clarify the specific mechanisms at work.

Overall, we see our results as broadly complementary to the work of Dunn and Shapiro (2016) insofar as they too document a connection between cardiology market concentration and increased utilization. However, we have found that concentration has a negative impact on clinical quality, while they find small improvements. The difference in our results may reflect differences in the populations studied as they consider effects on the commercially insured population, where prices are negotiated, while we focus on Medicare beneficiaries, where prices are set administratively. Alternatively, it may reflect our different identification strategies. They focus on patients who have suffered a heart attack and look for effects in the following 90 days – whereas we consider effects for patients seen for heart problems in the prior year. We hope that future research can reconcile our respective findings.

## V. CONCLUSION

In conclusion, our estimates indicate that increases in concentration in cardiology markets are associated with worse outcomes for patients but no significant offsetting efficiencies. This supports the implication of economic theory that competition matters in physician markets as well as the more often studied hospital markets. Moreover, it is consistent with the large literature documenting that physicians respond to their financial incentives, even if the consequences do not benefit patients (Coey, 2015; Chandra, Cutler, & Song, 2012; Hennig-

Schmidt, Selten, & Wiesen, 2011). Finally, our results suggest that antitrust agencies have reason for concern not just about price effects but also other forms of consumer harm from concentrated physician markets.[17]

[17] See, e.g., the remarks given by the FTC's Chairwoman at the Antitrust in Healthcare Conference in 2016 (https://www.ftc.gov/public-statements/2016/05/keynote-address-ftc-chairwoman-edith-ramirez, as accessed May 25, 2016).

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# VII. Online Appendix A: Data Description

## A. Data Sets

As stated in the text, we make use of the medical claims from a 5% sample of Medicare beneficiaries for the period between 2005 and 2012.[18] The claims are inclusive of inpatient admissions, hospital outpatient visits, and office-based visits. The Medicare data are contained in multiple separate datasets – Carrier, Outpatient, Inpatient, and Beneficiary Summary. Our analysis leverages elements from the Carrier, Outpatient, and Summary datasets.

Our research question is to assess the extent to which physician concentration affects patients' long-run health and utilization of health care services. It is our conjecture that the principal way that physician quality matters to these things is via prevention and maintenance. Therefore, our assessment of concentration is based on outpatient interactions as opposed to inpatient ones. We do not consider individual interactions in inpatient settings. This leads us to focus on one or both of the Carrier and Outpatient datasets.

For both datasets, we exploit CMS' definition of "base claims" to distinguish interactions. The relevant "base claim" aggregates over physician identifiers and CPT procedure codes.

When considering the effects of physician concentration, we do wish to include information on inpatient events. Therefore, we leverage the Beneficiary Summary files to consider total overall expenditures and the incidence of certain major health events (heart attacks, etc.).

## B. Analytical Dataset Construction

### *i. Identifying Cardiology Interactions*

To identify cardiologists, we exploit the classification performed by CMS of different physicians. In the Carrier files, each physician is identified with a unique identifier. Both the UPIN and NPI identifiers are used. Irrespective of identifier, each physician is also categorized by a specialty (PRVDR_SPCLTY) number.

For each year of our data, we create a list of the physician identifiers associated with specialty number 6, which is for cardiology. We then flag all base claims involving these physicians in either the Carrier or Outpatient files.

### *ii. Different Inputs to Concentration Calculation*

Our baseline approach to constructing concentration measures is to weight interactions between cardiologists and their patients by the allowed spending going on. We believe that this is reasonable as a baseline, but perform a variety of robustness checks based on alternative assumptions to ensure that conclusions are not sensitive. In particular, we construct alternative measures of market competitiveness using the number of clinical evaluation/management services (CPT codes 99201-99245; hereafter, "clinical") claims.

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[18] The sample represents 5% of Medicare recipients. The sample does not address selection associated with Medicare Advantage plans, which compete with traditional Medicare. Unfortunately, claims for Medicare Advantage plans, and privately-insured plans more generally, are not widely available.

As discussed in other research (Koch, Wendling, & Wilson, forthcoming), there are grounds to believe that some true events claims are duplicated in the Carrier and Outpatient files. We believe a focus on the allowed amount when constructing our concentration measure helps to address this concern. However, to avoid any possibility of double-counting, we also consider if our results are sensitive to recalculating concentration measures based on the Carrier files. We have not found our qualitative conclusions to be sensitive to such variation.

*iii. Assigning Physicians to Decision-makers*

We assign individual physicians to the decision-makers based on the Tax Number they are linked to. Unfortunately, this linkage is only present in the Carrier files. Therefore, for the Outpatient interactions, we use the modal Tax Number associated with each NPI and/or UPIN in the Carrier files. To the extent that physicians change organizations over time, this will introduce measurement error into our concentration variables, and thereby attenuate our estimates of its impact. Thus, it is a conservative approach.

*iv. Defining Different Patient Samples*

As described in the text, we consider how effects change across different populations. We define these populations using health information from patients' ICD9 diagnoses. Hypertensive patients are identified as those with hypertension in its 5-digit ICD-9 code description. This definition includes all ICD-9 codes with prefixes 401, 405, and 459.3. Notably, our definition also includes ICD-9 code 796.20, which is elevated blood pressure without diagnosis of hypertension.

*v. Cleaning Samples and Variable Definition*

i. Demographics

Gender identified from BENE_SEX. Focus limited to those categorized consistently as either male or female.

Race inferred from BENE_RACE. Race is allowed to vary over time. Missing variables are imputed to be the mode for non-missing years for that patient. Patients with no race information are dropped.

Age is calculated as the difference between the year of the claim and the patient's year of birth (BENE_BIRTH_DT). We restrict attention to observations for beneficiaries who are at least 60 years old and who are less than 100. The age variable is discretized by-five year blocks.

Residence is defined based on the patient zip-code information that is present in the beneficiary summary files. We focus on the zip-code. We also exploit the county identifier in the data files.

When constructing our non-parametric demographic controls, we simultaneously interact county with our gender, age, and race groups. This allows us to richly control for differences in seemingly observably similar patients across different geographies while also imposing no linear assumptions on how age impacts health outcomes or utilization.

ii. Death

To construct the mortality variable, we use the "date of death" information in the Beneficiary file (BENE_DEATH_DT). If the year for this variable matches the year for the beneficiary in our sample, they are categorized as having died that year. All observations for beneficiaries for dates after that in which they are evaluated as having died are dropped.

iii. Heart Attacks

For the AMI variable, we exploit the "Acute Myocardial Infarction End-of-Year Flag" in the Beneficiary file (AMI). We limit attention to patients whose claims and coverage met the criteria CMS defines for the condition. The AMI sample is defined as the set of patients who in that year or a prior observed one met the criteria.

iv. Other Outcome Variables

The other outcome measures were also taken from the Beneficiary file or derived from information therein. Specifically, hospital expenditures were defined as the sum of hospital inpatient (acute or otherwise) and outpatient expenditures by either CMS or the beneficiary themselves (HOP_MDCR_PMT, HOP_BENE_PMT, OIP_MDCR_PMT, OIP_BENE_PMT, ACUTE_MDCR_PMT, ACUTE_BENE_PMT).

Doctor expendituress were defined as the sum of payments to physicians by either CMS or the beneficiary (PHYS_MDCR_PMT, PHYS_BENE_PMT).

Days spent in the hospital were defined as the sum of acute and other inpatient days (OIP_COV_DAYS, ACUTE_COV_DAYS+1).

Visits to the emergency room were defined as the sum of visits to either outpatient or inpatient ERs (HOP_ER_VISITS, IP_ER_VISITS).

v. Comorbidities

ESRD patients were identified by the BENE_ESRD variable. We assume it to be an absorbing state. In other words, once a beneficiary is identified as suffering from ESRD, that variable is permanently turned on in our analysis.

Type 2 diabetes sufferers are identified using the ICD9 codes associated with patient claims. Once more, we assume it to be an absorbing state. The specific ICD9 codes we use to identify diabetic beneficiaries are:

250.00-250.03 diabetes mellitus without mention of complication 0

250.10-250.13 diabetes with ketoacidosis 1

250.20-250.23 diabetes with hyperosmolarity 1

250.30-250.33 diabetes with unspecified complication 1

250.40-250.43 diabetes with other coma 2

250.50-250.53 diabetes with renal manifestations 2

250.60-250.63 diabetes with ophthalmic manifestations 2

250.70-250.73 diabetes with neurological manifestations 2

250.80-250.83 diabetes with peripheral circulatory disorders 2

250.90-250.93 diabetes with other specified manifestations 2

## VIII. ONLINE APPENDIX B: ROBUSTNESS RESULTS

**Figure 3: Histogram of Coefficient of Variation Across Zip-codes**

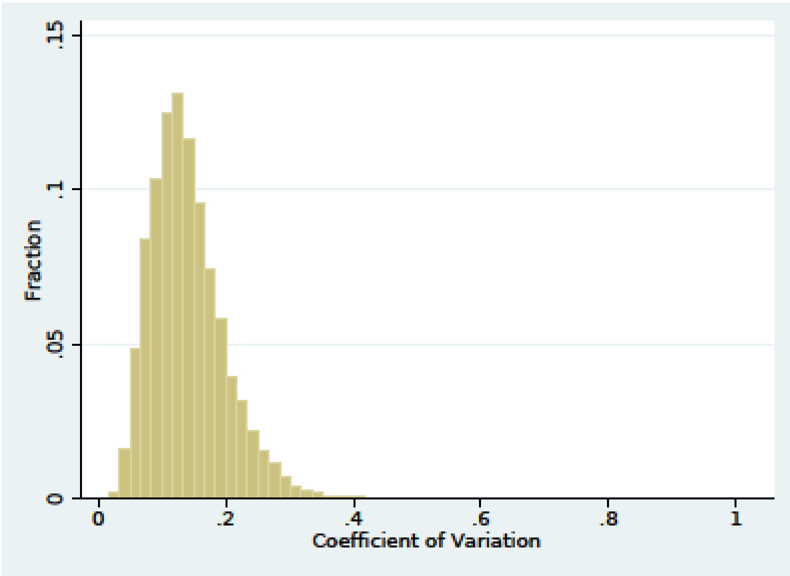

**Table 4: Quality Results with Non-Parametric Demographic Controls**

| Sample | Died | AMI | 1(ER) | Log(Readmissions + 1) | N |
|---|---|---|---|---|---|
| **Hyper** | 0.012*** | 0.003*** | 0.033*** | 0.007*** | 7616752 |
| **Chronic** | 0.009*** | 0.002** | 0.028*** | 0.004** | 4651140 |
| **Acute** | 0.014*** | 0.001 | 0.033*** | 0.007*** | 4316207 |
| **AMI** | -0.007 | 0.033 | 0.104** | 0.013 | 79218 |

Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. * p<0.1; ** p<0.05; *** p<0.01.

**Table 5: Utilization Results with Non-Parametric Demographic Controls**

| Sample | Log(Total Expenditures+1) | Log(Hosp Expenditures+1) | Log(Phys Expenditures+1) | Log(Hosp Days+1) | N |
|---|---|---|---|---|---|
| **Hyper** | 0.288*** | 0.582*** | -0.054*** | 0.040*** | 7476690 |
| **Chronic** | 0.190*** | 0.543*** | -0.108*** | 0.030*** | 4590240 |
| **Acute** | 0.216*** | 0.564*** | -0.124*** | 0.049*** | 4260140 |
| **AMI** | 0.329* | 0.738*** | 0.192 | 0.167 | 70817 |

Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. * $p<0.1$; ** $p<0.05$; *** $p<0.01$.

**Table 6: Quality Results where HHIs Based on Visits**

| Sample | Died | AMI | 1(ER) | Log(Readmissions + 1) | N |
|---|---|---|---|---|---|
| **Hyper** | 0.006*** | 0.001+ | 0.025*** | 0.002 | 7530942 |
| **Chronic** | 0.005*** | 0.001 | 0.021*** | 0.002 | 4599906 |
| **Acute** | 0.007*** | -0.001 | 0.028*** | 0.002 | 4268262 |
| **AMI** | -0.013 | 0.013 | 0.129*** | 0.013 | 78406 |

Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. * p<0.1; ** p<0.05; *** p<0.01.

**Table 7: Utilization Results where HHIs Based on Visits**

| Sample | Log(Total Expenditures+1) | Log(Hosp Expenditures+1) | Log(Phys Expenditures+1) | Log(Hosp Days+1) | N |
|---|---|---|---|---|---|
| **Hyper** | 0.144*** | 0.372*** | -0.069*** | 0.015* | 7530942 |
| **Chronic** | 0.079*** | 0.337*** | -0.098*** | 0.020** | 4599906 |
| **Acute** | 0.107*** | 0.382*** | -0.114*** | 0.029*** | 4268262 |
| **AMI** | 0.553*** | 0.772*** | 0.236 | 0.243** | 78406 |

Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. * p<0.1; ** p<0.05; *** p<0.01.

## Table 8: Full Regression Results for Hypertensive Sample

| | Died | AMI | Log(Read +1) | 1(ER) | Log(Hosp Expenditures+1 ) | Log(Phys Expenditures+1 ) | Log(Total Expenditures+1 ) | Log(Hosp Days+1) |
|---|---|---|---|---|---|---|---|---|
| lagadj | 0.012*** | 0.003*** | 0.007*** | 0.033*** | 0.629*** | -0.011 | 0.344*** | 0.043*** |
| | 0.002 | 0.001 | 0.002 | 0.004 | 0.03 | 0.02 | 0.021 | 0.007 |
| 1.lagesrd | 0.175*** | 0.034*** | 0.189*** | 0.349*** | 4.302*** | 0.006 | 3.025*** | 1.018*** |
| | 0.002 | 0.001 | 0.002 | 0.002 | 0.017 | 0.013 | 0.013 | 0.007 |
| 1.lagdiab | 0.020*** | 0.006*** | 0.022*** | 0.075*** | 0.617*** | 0.193*** | 0.456*** | 0.167*** |
| | 0 | 0 | 0 | 0 | 0.004 | 0.003 | 0.003 | 0.001 |
| Black | 0 | -0.002*** | 0.003*** | 0.038*** | -0.109*** | -0.559*** | -0.316*** | 0.002 |
| | 0 | 0 | 0 | 0.001 | 0.01 | 0.008 | 0.007 | 0.002 |
| Other | -0.012*** | -0.002*** | -0.009*** | -0.029*** | -0.401*** | -0.212*** | -0.243*** | -0.099*** |
| | 0 | 0 | 0 | 0.001 | 0.014 | 0.01 | 0.008 | 0.003 |
| Female | -0.017*** | -0.004*** | -0.005*** | 0.012*** | 0.249*** | 0.009*** | 0.035*** | -0.023*** |
| | 0 | 0 | 0 | 0 | 0.004 | 0.003 | 0.003 | 0.001 |
| 65.agecat | -0.005*** | -0.002*** | -0.018*** | -0.111*** | -0.646*** | 0.037*** | -0.315*** | -0.152*** |
| | 0 | 0 | 0.001 | 0.001 | 0.01 | 0.007 | 0.007 | 0.003 |
| 70.agecat | 0.001** | -0.001*** | -0.016*** | -0.099*** | -0.468*** | 0.179*** | -0.154*** | -0.120*** |
| | 0 | 0 | 0.001 | 0.001 | 0.01 | 0.007 | 0.007 | 0.003 |
| 75.agecat | 0.016*** | 0.001*** | -0.007*** | -0.055*** | -0.170*** | 0.239*** | 0.041*** | -0.030*** |
| | 0 | 0 | 0.001 | 0.001 | 0.01 | 0.007 | 0.007 | 0.003 |
| 80.agecat | 0.040*** | 0.004*** | 0.002*** | 0.004*** | 0.046*** | 0.156*** | 0.175*** | 0.072*** |
| | 0 | 0 | 0.001 | 0.001 | 0.01 | 0.007 | 0.008 | 0.003 |
| 85.agecat | 0.080*** | 0.008*** | 0.012*** | 0.068*** | 0.208*** | -0.126*** | 0.234*** | 0.182*** |
| | 0.001 | 0 | 0.001 | 0.001 | 0.011 | 0.008 | 0.008 | 0.003 |
| 90.agecat | 0.142*** | 0.013*** | 0.017*** | 0.122*** | 0.301*** | -0.667*** | 0.185*** | 0.266*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.012 | 0.009 | 0.009 | 0.003 |
| 95.agecat | 0.227*** | 0.016*** | 0.019*** | 0.147*** | 0.341*** | -1.435*** | 0.015+ | 0.308*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.016 | 0.014 | 0.012 | 0.004 |
| 2007.year | -0.002*** | -0.001*** | -0.002*** | -0.006*** | -0.072*** | 0.003+ | -0.052*** | -0.022*** |
| | 0 | 0 | 0 | 0.001 | 0.004 | 0.003 | 0.003 | 0.001 |
| 2008.year | -0.002*** | -0.001*** | -0.003*** | -0.007*** | -0.112*** | -0.017*** | -0.087*** | -0.034*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.003 | 0.004 | 0.001 |
| 2009.year | -0.004*** | -0.002*** | -0.006*** | -0.016*** | -0.174*** | -0.042*** | -0.163*** | -0.064*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.004 | 0.004 | 0.001 |
| 2010.year | -0.003*** | -0.002*** | -0.007*** | -0.015*** | -0.156*** | 0.137*** | -0.088*** | -0.075*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.004 | 0.004 | 0.001 |
| 2011.year | -0.003*** | -0.002*** | -0.008*** | -0.008*** | -0.070*** | 0.208*** | -0.004 | -0.083*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.004 | 0.004 | 0.001 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2012.year | -0.002*** | -0.002*** | -0.010*** | 0 | 0.023*** | 0.265*** | 0.076*** | -0.096*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.004 | 0.004 | 0.001 |
| _cons | 0.026*** | 0.009*** | 0.041*** | 0.321*** | 5.285*** | 5.246*** | 6.806*** | 0.450*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.013 | 0.009 | 0.009 | 0.004 |
| N | 7616752 | 7616752 | 7616752 | 7616752 | 7616752 | 7616752 | 7616752 | 7616752 |
| r2 | 0.05 | 0.01 | 0.025 | 0.051 | 0.082 | 0.09 | 0.054 | 0.051 |
| Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. + p<0.2; * p<0.1; ** p<0.05; *** p<0.01. | | | | | | | | |

## Table 9: Full Regression Results for Chronic Sample

| | Died | AMI | Log(Read +1) | 1(ER) | Log(Hosp Expenditures+1 ) | Log(Phys Expenditures+1 ) | Log(Total Expenditures+1 ) | Log(Hosp Days+1) |
|---|---|---|---|---|---|---|---|---|
| lagadj | 0.009*** | 0.002** | 0.004** | 0.028*** | 0.597*** | -0.064*** | 0.250*** | 0.032*** |
| | 0.002 | 0.001 | 0.002 | 0.005 | 0.036 | 0.021 | 0.023 | 0.009 |
| 1.lagesrd | 0.170*** | 0.034*** | 0.185*** | 0.354*** | 4.265*** | -0.047*** | 2.943*** | 1.018*** |
| | 0.002 | 0.001 | 0.003 | 0.003 | 0.021 | 0.016 | 0.015 | 0.01 |
| 1.lagdiab | 0.019*** | 0.006*** | 0.021*** | 0.083*** | 0.723*** | 0.289*** | 0.553*** | 0.174*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.003 | 0.003 | 0.001 |
| Black | 0.001** | -0.001*** | 0.004*** | 0.048*** | -0.007 | -0.453*** | -0.209*** | 0.013*** |
| | 0.001 | 0 | 0.001 | 0.001 | 0.012 | 0.009 | 0.008 | 0.003 |
| Other | -0.009*** | -0.002*** | -0.008*** | -0.025*** | -0.366*** | -0.237*** | -0.248*** | -0.086*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.016 | 0.011 | 0.009 | 0.003 |
| Female | -0.014*** | -0.004*** | -0.005*** | 0.010*** | 0.273*** | 0.013*** | 0.042*** | -0.025*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.003 | 0.003 | 0.001 |
| 65.agecat | -0.006*** | -0.001** | -0.017*** | -0.126*** | -0.820*** | -0.056*** | -0.443*** | -0.168*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.014 | 0.01 | 0.01 | 0.004 |
| 70.agecat | -0.002** | 0 | -0.016*** | -0.115*** | -0.657*** | 0.077*** | -0.294*** | -0.142*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.014 | 0.01 | 0.01 | 0.004 |
| 75.agecat | 0.009*** | 0.002*** | -0.009*** | -0.072*** | -0.365*** | 0.165*** | -0.092*** | -0.061*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.014 | 0.01 | 0.01 | 0.004 |
| 80.agecat | 0.028*** | 0.005*** | 0 | -0.013*** | -0.155*** | 0.144*** | 0.056*** | 0.037*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.015 | 0.01 | 0.01 | 0.004 |
| 85.agecat | 0.062*** | 0.009*** | 0.011*** | 0.055*** | 0.026* | -0.045*** | 0.152*** | 0.154*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.015 | 0.011 | 0.01 | 0.004 |
| 90.agecat | 0.118*** | 0.014*** | 0.018*** | 0.120*** | 0.152*** | -0.495*** | 0.147*** | 0.256*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.016 | 0.012 | 0.011 | 0.005 |
| 95.agecat | 0.199*** | 0.017*** | 0.021*** | 0.151*** | 0.214*** | -1.230*** | 0.008 | 0.312*** |
| | 0.002 | 0.001 | 0.001 | 0.003 | 0.021 | 0.017 | 0.015 | 0.006 |
| 2007.year | -0.001*** | -0.001*** | -0.002*** | -0.006*** | -0.061*** | 0.024*** | -0.030*** | -0.021*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.003 | 0.004 | 0.001 |
| 2008.year | -0.002*** | -0.001*** | -0.003*** | -0.007*** | -0.083*** | 0.026*** | -0.040*** | -0.032*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.004 | 0.004 | 0.002 |
| 2009.year | -0.003*** | -0.001*** | -0.005*** | -0.011*** | -0.053*** | 0.083*** | -0.003 | -0.051*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.004 | 0.004 | 0.002 |
| 2010.year | -0.004*** | -0.002*** | -0.006*** | -0.009*** | -0.026*** | 0.284*** | 0.097*** | -0.063*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.004 | 0.002 |
| 2011.year | -0.004*** | -0.002*** | -0.007*** | -0.004*** | 0.041*** | 0.336*** | 0.154*** | -0.073*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.005 | 0.002 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2012.year | -0.004*** | -0.002*** | -0.009*** | 0.002** | 0.105*** | 0.367*** | 0.202*** | -0.086*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.004 | 0.002 |
| _cons | 0.022*** | 0.007*** | 0.037*** | 0.313*** | 5.360*** | 5.397*** | 6.885*** | 0.423*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.017 | 0.012 | 0.012 | 0.005 |
| N | 4651140 | 4651140 | 4651140 | 4651140 | 4651140 | 4651140 | 4651140 | 4651140 |
| r2 | 0.05 | 0.013 | 0.028 | 0.058 | 0.089 | 0.097 | 0.062 | 0.057 |
| Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. + p<0.2; * p<0.1; ** p<0.05; *** p<0.01. | | | | | | | | |

## Table 10: Full Regression Results for Acute Sample

| | Died | AMI | Log(Read +1) | 1(ER) | Log(Hosp Expenditures+1 ) | Log(Phys Expenditures+1 ) | Log(Total Expenditures+1 ) | Log(Hosp Days+1) |
|---|---|---|---|---|---|---|---|---|
| lagadj | 0.014*** | 0.001 | 0.007*** | 0.033*** | 0.625*** | -0.079*** | 0.282*** | 0.052*** |
| | 0.002 | 0.001 | 0.002 | 0.005 | 0.036 | 0.022 | 0.024 | 0.009 |
| 1.lagesrd | 0.178*** | 0.036*** | 0.194*** | 0.343*** | 4.141*** | -0.135*** | 2.854*** | 1.033*** |
| | 0.002 | 0.001 | 0.003 | 0.003 | 0.02 | 0.015 | 0.015 | 0.009 |
| 1.lagdiab | 0.022*** | 0.006*** | 0.024*** | 0.087*** | 0.734*** | 0.255*** | 0.543*** | 0.191*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.003 | 0.003 | 0.001 |
| Black | 0 | -0.001*** | 0.005*** | 0.053*** | 0.032*** | -0.437*** | -0.177*** | 0.023*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.012 | 0.009 | 0.008 | 0.003 |
| Other | -0.011*** | -0.002*** | -0.008*** | -0.027*** | -0.393*** | -0.213*** | -0.241*** | -0.093*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.016 | 0.011 | 0.008 | 0.003 |
| Female | -0.016*** | -0.004*** | -0.005*** | 0.013*** | 0.276*** | 0.036*** | 0.054*** | -0.024*** |
| | 0 | 0 | 0 | 0.001 | 0.005 | 0.003 | 0.003 | 0.001 |
| 65.agecat | -0.005*** | -0.001*** | -0.017*** | -0.125*** | -0.771*** | -0.052*** | -0.413*** | -0.163*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.013 | 0.009 | 0.009 | 0.004 |
| 70.agecat | -0.001 | -0.001+ | -0.015*** | -0.112*** | -0.584*** | 0.092*** | -0.245*** | -0.132*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.013 | 0.009 | 0.009 | 0.004 |
| 75.agecat | 0.011*** | 0.002*** | -0.008*** | -0.067*** | -0.272*** | 0.180*** | -0.034*** | -0.045*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.013 | 0.009 | 0.009 | 0.004 |
| 80.agecat | 0.032*** | 0.004*** | 0.002** | -0.007*** | -0.059*** | 0.139*** | 0.109*** | 0.057*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.013 | 0.009 | 0.009 | 0.004 |
| 85.agecat | 0.068*** | 0.008*** | 0.012*** | 0.060*** | 0.115*** | -0.085*** | 0.189*** | 0.172*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.014 | 0.009 | 0.009 | 0.004 |
| 90.agecat | 0.127*** | 0.013*** | 0.019*** | 0.118*** | 0.219*** | -0.584*** | 0.156*** | 0.267*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.015 | 0.011 | 0.01 | 0.004 |
| 95.agecat | 0.211*** | 0.017*** | 0.020*** | 0.146*** | 0.250*** | -1.366*** | -0.018 | 0.315*** |
| | 0.002 | 0.001 | 0.001 | 0.003 | 0.019 | 0.016 | 0.014 | 0.006 |
| 2007.year | -0.002*** | -0.001*** | -0.002*** | -0.006*** | -0.056*** | 0.031*** | -0.028*** | -0.022*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.003 | 0.004 | 0.002 |
| 2008.year | -0.003*** | -0.001*** | -0.003*** | -0.007*** | -0.082*** | 0.027*** | -0.041*** | -0.034*** |
| | 0 | 0 | 0 | 0.001 | 0.006 | 0.004 | 0.004 | 0.002 |
| 2009.year | -0.004*** | -0.001*** | -0.005*** | -0.011*** | -0.059*** | 0.086*** | -0.005 | -0.055*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.004 | 0.002 |
| 2010.year | -0.005*** | -0.002*** | -0.007*** | -0.010*** | -0.040*** | 0.283*** | 0.083*** | -0.070*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.005 | 0.002 |
| 2011.year | -0.005*** | -0.002*** | -0.008*** | -0.005*** | 0.025*** | 0.337*** | 0.142*** | -0.080*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.005 | 0.002 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2012.year | -0.004*** | -0.002*** | -0.010*** | 0 | 0.082*** | 0.366*** | 0.184*** | -0.096*** |
| | 0 | 0 | 0 | 0.001 | 0.007 | 0.004 | 0.005 | 0.002 |
| _cons | 0.022*** | 0.008*** | 0.038*** | 0.324*** | 5.377*** | 5.421*** | 6.899*** | 0.428*** |
| | 0.001 | 0 | 0.001 | 0.002 | 0.017 | 0.011 | 0.011 | 0.005 |
| N | 4316207 | 4316207 | 4316207 | 4316207 | 4316207 | 4316207 | 4316207 | 4316207 |
| r2 | 0.055 | 0.014 | 0.031 | 0.061 | 0.092 | 0.098 | 0.064 | 0.062 |
| Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. + p<0.2; * p<0.1; ** p<0.05; *** p<0.01. | | | | | | | | |

## Table 11: Full Regression Results for AMI Sample

| | Died | AMI | Log(Read +1) | 1(ER) | Log(Hosp Expenditures+1 ) | Log(Phys Expenditures+1 ) | Log(Total Expenditures+1 ) | Log(Hosp Days+1) |
|---|---|---|---|---|---|---|---|---|
| lagadj | -0.007 | 0.033 | 0.013 | 0.104** | 0.790*** | 0.245 | 0.430** | 0.178+ |
| | 0.035 | 0.026 | 0.034 | 0.048 | 0.296 | 0.213 | 0.21 | 0.116 |
| 1.lagesrd | 0.235*** | 0.061*** | 0.251*** | 0.261*** | 3.219*** | -0.356*** | 2.380*** | 0.974*** |
| | 0.012 | 0.009 | 0.014 | 0.01 | 0.059 | 0.06 | 0.043 | 0.036 |
| 1.lagdiab | 0.048*** | 0.030*** | 0.059*** | 0.090*** | 0.680*** | 0.054** | 0.469*** | 0.313*** |
| | 0.003 | 0.002 | 0.003 | 0.005 | 0.033 | 0.021 | 0.022 | 0.012 |
| Black | 0.011 | 0.010* | 0.026*** | 0.055*** | 0.235*** | -0.424*** | 0.071+ | 0.134*** |
| | 0.008 | 0.006 | 0.008 | 0.011 | 0.076 | 0.053 | 0.053 | 0.03 |
| Other | -0.012 | 0.012* | -0.006 | -0.002 | -0.028 | -0.130** | -0.006 | -0.031 |
| | 0.01 | 0.007 | 0.01 | 0.013 | 0.093 | 0.064 | 0.063 | 0.035 |
| Female | -0.016*** | -0.007*** | 0.013*** | 0.054*** | 0.310*** | -0.045** | 0.139*** | 0.088*** |
| | 0.004 | 0.003 | 0.003 | 0.005 | 0.032 | 0.021 | 0.022 | 0.012 |
| 65.agecat | -0.002 | -0.019** | -0.037*** | -0.095*** | -0.280*** | 0.176*** | -0.099+ | -0.148*** |
| | 0.01 | 0.008 | 0.012 | 0.014 | 0.1 | 0.067 | 0.071 | 0.039 |
| 70.agecat | 0.003 | -0.019** | -0.035*** | -0.087*** | -0.163* | 0.293*** | -0.024 | -0.118*** |
| | 0.01 | 0.008 | 0.012 | 0.014 | 0.098 | 0.066 | 0.07 | 0.038 |
| 75.agecat | 0.039*** | -0.008 | -0.030** | -0.050*** | 0.081 | 0.246*** | 0.126* | -0.015 |
| | 0.01 | 0.008 | 0.012 | 0.014 | 0.096 | 0.065 | 0.068 | 0.038 |
| 80.agecat | 0.082*** | -0.004 | -0.026** | -0.007 | 0.142+ | 0.053 | 0.156** | 0.055+ |
| | 0.01 | 0.008 | 0.012 | 0.014 | 0.096 | 0.066 | 0.068 | 0.038 |
| 85.agecat | 0.149*** | 0.009 | -0.020+ | 0.035** | 0.159+ | -0.374*** | 0.109+ | 0.139*** |
| | 0.01 | 0.008 | 0.012 | 0.014 | 0.098 | 0.068 | 0.07 | 0.038 |
| 90.agecat | 0.227*** | 0.029*** | -0.005 | 0.061*** | 0.071 | -0.947*** | -0.062 | 0.180*** |
| | 0.011 | 0.008 | 0.013 | 0.015 | 0.104 | 0.074 | 0.076 | 0.041 |
| 95.agecat | 0.297*** | 0.026** | -0.019 | 0.066*** | -0.159 | -1.754*** | -0.425*** | 0.142*** |
| | 0.016 | 0.011 | 0.015 | 0.019 | 0.133 | 0.099 | 0.102 | 0.05 |
| 2007.year | 0.005 | -0.003 | -0.004 | -0.002 | -0.058 | 0.008 | -0.021 | -0.023 |
| | 0.006 | 0.005 | 0.006 | 0.008 | 0.055 | 0.035 | 0.038 | 0.02 |
| 2008.year | 0.015** | -0.007+ | 0.005 | 0.013+ | 0.094+ | 0.001 | 0.075* | 0.005 |
| | 0.006 | 0.005 | 0.006 | 0.009 | 0.058 | 0.038 | 0.04 | 0.022 |
| 2009.year | 0.005 | -0.013*** | -0.001 | -0.002 | 0.036 | 0.122*** | 0.088** | -0.061*** |
| | 0.007 | 0.005 | 0.007 | 0.009 | 0.059 | 0.039 | 0.041 | 0.022 |
| 2010.year | 0.016** | -0.011** | -0.008 | 0.011 | 0.113* | 0.261*** | 0.167*** | -0.063*** |
| | 0.007 | 0.005 | 0.007 | 0.009 | 0.061 | 0.04 | 0.041 | 0.023 |
| 2011.year | 0.012* | -0.011** | -0.003 | 0.01 | 0.134** | 0.323*** | 0.181*** | -0.078*** |
| | 0.007 | 0.005 | 0.007 | 0.009 | 0.06 | 0.04 | 0.041 | 0.023 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| 2012.year | 0.014** | -0.013*** | -0.017** | 0.021** | 0.222*** | 0.398*** | 0.232*** | -0.100*** |
| | 0.007 | 0.005 | 0.007 | 0.009 | 0.061 | 0.041 | 0.042 | 0.024 |
| _cons | 0.054*** | 0.056*** | 0.105*** | 0.457*** | 6.322*** | 5.405*** | 7.476*** | 0.736*** |
| | 0.014 | 0.011 | 0.015 | 0.019 | 0.128 | 0.089 | 0.091 | 0.049 |
| N | 79218 | 79218 | 79218 | 79218 | 79218 | 79218 | 79218 | 79218 |
| r2 | 0.285 | 0.23 | 0.274 | 0.287 | 0.3 | 0.315 | 0.307 | 0.3 |
| Notes: Cells contain the estimated coefficient on the concentration measure. Standard errors were clustered at the zip-code level. + p<0.2; * p<0.1; ** p<0.05; *** p<0.01. | | | | | | | | |