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The Impact of Medicare Insurance Plans upon Healthcare Services Utilization Considering Patients' Characteristics and Their Access to Medical Care

Steven Stout
University of Missouri-St. Louis, srsfk3@umsystem.edu

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Steven R. Stout

M.B.A., Washington University, 1992
B.S., Communication, St. Louis University, 1980

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Advisory Committee

James F. Campbell, Ph.D.
Chairperson

L. Douglas Smith, Ph.D.

Dinesh Mirchandani, Ph.D.

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Abstract

The annual average cost of healthcare for services utilization by a Medicare beneficiary is projected to grow from about $10,000 to over $16,000 by 2023. As an ongoing initiative to address this trend, the federal government contracts with private insurance companies and other entities, called Medicare Advantage Organizations (MAOs), to develop and administer alternative health insurance plans designed to contain service utilization and costs. One feature of some Medicare Advantage plans is the presence of risk-bearing contracts with primary care physician organizations that voluntarily accept financial responsibility for the overall cost of care for patients attributed to them. In this arrangement, the MAO delegates medical care, care management oversight, and discretionary spending authority to the physician organization. For services rendered, the physician organization accepts as payment the surplus or deficit derived from annual budgetary results (as negotiated in their contract with the MAO) rather than the traditional per-encounter or service-specific payments associated with fee-for-service payment schemes. This study uses an extensive and novel data set from the Centers for Medicare and Medicaid Services, as well as third-party sources, to examine how Missouri beneficiary's attributes (age, gender, race, and health status), presumed financial resources and education, access to doctors and hospitals, and Medicare plan choices help to predict services utilization. We use summary statistics, tests of differences in means, CHAID decision trees, and Poisson regression to analyze beneficiaries' utilization of five service categories (inpatient care, skilled nursing care, outpatient services, home health services, and other provider services, including physicians). The study reveals three critical findings. First, specific beneficiary attributes such as age and race, and beneficiary access to doctors and hospitals are predictors of one's chosen Medicare plan. Notably, some Medicare beneficiary groups are more likely to enroll in a Medicare Advantage plan rather than others. Second, beneficiary characteristics, doctor and hospital access, and plan choice collectively have a strong association with service utilization. Those enrolled in Medicare Advantage plans use fewer services than their Traditional Medicare counterparts. Lastly, beneficiaries enrolled in a Medicare Advantage plan that engages risk-bearing primary care physician groups use fewer services than beneficiaries in other plans.

Keywords: Medicare, Advantage, health insurance, utilization, risk, contracts, physicians, capitation

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Glossary

CMS – Centers for Medicare and Medicaid Services

CPT – Current Procedural Terminology

DRG – Diagnostic Related Group

FFS – Fee-for-Service

HCPCS – Healthcare Common Procedure Coding System

HHS – U.S. Department of Health and Human Services

HMO – Health Maintenance Organization

ICD – International Classification of Diseases (Versions 9 & 10)

IPA – Independent Physician Organization

MA – Medicare Advantage

MAC – Medicare Administrative Contractors

OECD – Organization for Economic Co-operation and Development

PCP – Primary Care Physician

PPO – Preferred Provider Organization

RB – Risk-bearing

TM – Traditional Medicare

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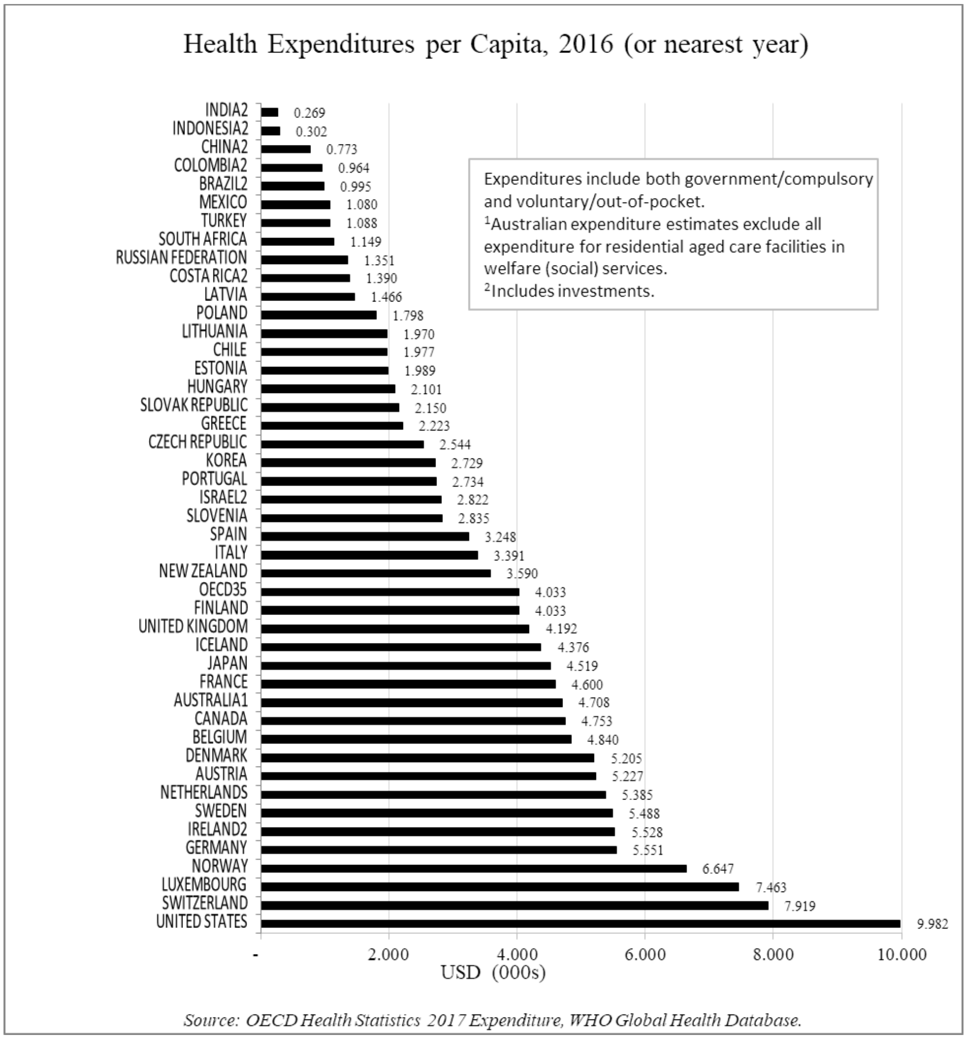
Chapter 1: Introduction and Scope

The United States has the most expensive health care system of any developed nation (Nahass and Rodriguez, 2015). As shown in Exhibit 1, its nearly $10,000 per capita, annual health expenditure far exceeds that of the other thirty-four members of the Organization for Economic Co-operation and Development (OECD). The U.S. costs per capita are more than twice the OECD average.

Furthermore, U.S. healthcare costs are escalating, in part, because of an increasing population of older adults who receive health insurance from a federal government program known as Medicare. Annual Medicare expenditures are projected to exceed one trillion dollars by 2023, equating to more than $16,000 per beneficiary per year (Keehan et al., 2020). To help combat these rising healthcare service costs, the government's Centers for Medicare and Medicaid Services (CMS) has implemented a strategy of encouraging Medicare-eligible beneficiaries to enroll in Medicare Advantage plans, also known as Medicare Part C, rather than the Traditional Medicare program.

Exhibit 1. Annual Per Capita Healthcare Expenditures for 35 OECD Countries



To implement its strategy, CMS, as the principal, relies on contracts with private insurers, known as Medicare Advantage Organizations (MAOs), who serve as CMS' agents and accept the operational and financial risk of their attributed enrollees. MAOs, in the role of principals, seek to delegate clinical care duties and shift financial risk to their agents, which include risk-bearing (RB) providers such as primary care physician

(PCP) groups. MAOs and RB providers understand that their financial success is dependent on effective management of patient services.

CMS mandates that Medicare Advantage beneficiaries receive equal or better benefits than those received by beneficiaries in the Traditional Medicare plan. Also, MAOs are required to meet or exceed standards imposed by CMS to assure that beneficiaries receive adequate access to healthcare providers and services. In response to those mandates, many MAOs offer plan features that include expanded benefits schedules at lower costs, thus enticing beneficiaries both to enroll in their Medicare Advantage plans and to engage in better health practices.

MAOs receive a fixed monthly payment from CMS for each beneficiary enrolled in their plans, thus placing the MAO at financial risk for the volume and cost of services attributable to its insured members. MAOs create service delivery networks in part by entering into agreements with medical providers who render services in exchange for payment. Payment methods vary and may include fee-for-service (FFS), modified FFS, capitation, or other RB arrangements.

FFS payments originate from pre-determined fee schedules that typically are the product of negotiations between MAOs and providers. An FFS payment generally is a one-time-only, lump-sum payment for a service such as a surgical facility fee or physician office visit. In this arrangement, there is little compensation risk to the provider because a known payment amount is earned for a rendered service.

Modified FFS payments sometime incorporate both lump-sum payments and bonus payments based on the achievement of pre-defined metrics. For example, a

PCP might receive from the MAO a $100 payment for rendering a comprehensive physical examination to a patient during an office visit, and then later receive a $50 bonus from the MAO for submitting written documentation that the patient received all required elements of that comprehensive exam. In this hypothetical example, a third of the physician's potential compensation is subject to risk (e.g., failure to satisfy the comprehensive exam requirements, not submitting appropriate documentation).

Capitation typically takes the form of a negotiated, monthly payment to a physician, physician group, health system, or other provider entity for each patient assigned to the entity. The capitation payment is expected to cover the costs of a defined schedule of medical services, both within and outside the entity, available to the patient. If the patient's medical costs exceed the capitation amount, the entity is responsible for paying for the excess. If the costs are less than the capitation amount, the entity enjoys retention of the surplus. In effect, the MAO transfers to the entity the financial risks attributable to patient care costs predicted by the capitation payment. The entity accepts that risk with an expectation that medical services and costs can be managed more efficiently than the capitation payment implies. In some arrangements, the MAO also may supplement the capitation payments with incentive bonuses tied to the achievement of clinical outcomes or utilization benchmarks associated with the pool of attributed patients. These supplemental payments can link to such metrics as the percentage of patients complying with prescribed medications, the percentage of male patients receiving annual prostate cancer screenings, or the percentage of female patients receiving mammograms.

Another form of capitation agreement occurs when an MAO and provider enter into a shared-risk arrangement. In this scenario, each party accepts a percentage of the deficits or surpluses stemming from the capitation revenue and medical costs of the attributed patients. In Appendix A, we present a discussion of how RB payment methods between MAOs and the PCPs in their networks are structured.

In this introduction, we highlighted several elements of the Medicare health system that potentially influence healthcare service utilization. They include the steerage of beneficiaries from Traditional Medicare to Medicare Advantage plans, the financial risk shift from CMS to MAOs, the financial risk shift from MAOs to providers, and an expectation that efficient service utilization will yield favorable financial results. To these macro elements, we introduce other factors that potentially affect service utilization. They include beneficiary characteristics (e.g., age, gender, race, health status, wealth, and level of education) and access to providers (hospital proximity, number of physicians). Accordingly, we obtained data for all of these elements in our quest to understand their effects on service utilization. The sources and uses of data are described in Chapter 4.

1.1 Research Question

Recent literature and commentary suggest that, compared to Traditional Medicare, some MAOs deliver better outcomes at lower costs by emphasizing primary, preventative care, along with the elimination of duplicative or unnecessary services, or using less costly services and service providers (Bazemore, Phillips, Glazier, & Tepper, 2018; Curto, Einav, Finkelstein, Levin, & Bhattacharya, 2017; Landon, Zaslavsky, Saunders, Pawlson, Newhouse, & Ayanian, 2012; Pham &

Moffit, 2018). Also, to instill incentives for efficient care, some MAOs implement RB agreements with PCPs willing to forgo traditional FFS payments. As described later in this paper, there are considerable, practical difficulties in gaining access to the terms, conditions, and financial results attributable to RB agreements between MAOs and the PCPs in their networks. Therefore, researchers may find it challenging to conduct this portion of the research. Fortunately, our association with a network of PCPs receiving both FFS and RB payments provides a rare and invaluable opportunity to understand the structure of RB agreements, as well as the arrangements between CMS and MAOs. That knowledge is useful when interpreting the results from our quantitative analyses.

In summary, with this study, we attempt to answer our fundamental research question: What elements affect a Medicare beneficiary's utilization of healthcare services? Related to this primary research question are several corollary questions. Do specific beneficiary attributes help predict choice of Medicare plan? Does a beneficiary's access to doctors and hospitals relate to choice of Medicare plan? Does the Medicare plan chosen help to predict service utilization? Do beneficiary characteristics help to predict service utilization? Moreover, do Medicare Advantage plans with RB PCPs show lesser utilization than other plans?

To answer these questions, we obtained data from several sources. Our Medicare data come from CMS following a formal, multi-month application process designed to assure that research data are appropriately used and protected. We requested and received 2016 health records for a random sample of 999,999 beneficiaries residing in the state of Missouri. At the time of this investigation, 2016 is the only year with the comprehensive Medicare data. For the identification and location of Missouri hospitals, we use public data from the Missouri Department of Health and Senior Services' Office of Primary Care and Rural Health. The Missouri Department of Professional Registrations is our data source for identifying the locations of licensed physicians. Lastly, through the University of Missouri Office of Social and Economic Data Analysis, we obtained Missouri demographical data distributed by the U.S. Bureau of the Census. Discussion of the sources and uses of data are contained in Chapter 4.

Summary statistics, tests of differences in means, CHAID decision trees, and Poisson regression are used to evaluate service utilization patterns influenced by patient characteristics, access to healthcare providers (hospitals and doctors), and choice of Medicare plan types. We also look for evidence to determine if the presence of RB PCPs in a Medicare Advantage plan impacts the number of healthcare services received by beneficiaries in that plan.

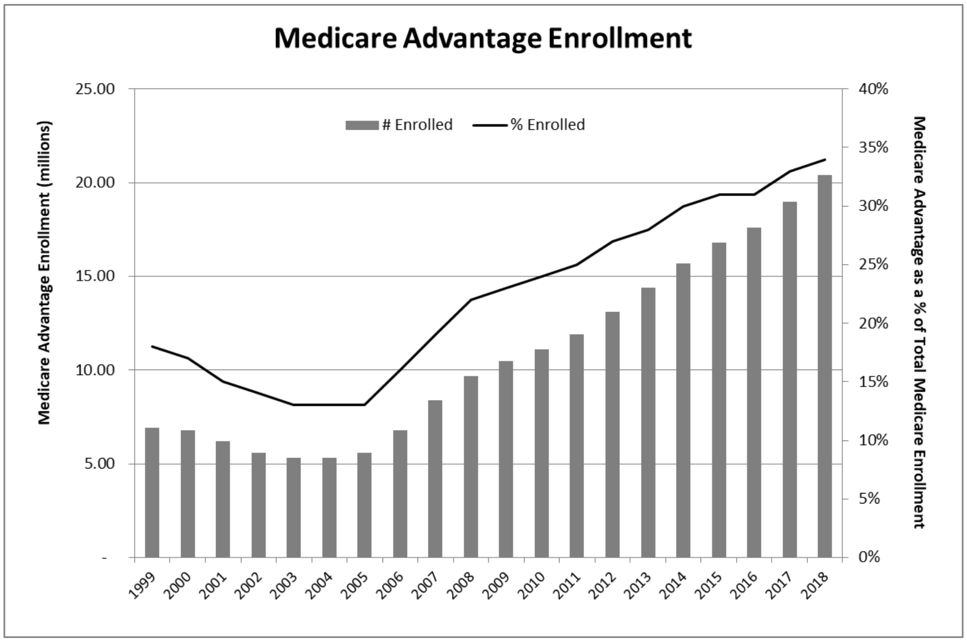
1.2 Significance

The Medicare program, a federal health insurance program administered by the United States Department of Health and Human Services'(HHS) Centers for Medicare and Medicaid Services (CMS), provides health insurance coverage to nearly 60 million U.S. residents: approximately 50 million people ages 65 and over, and 10 million people with permanent disabilities (KFF, 2018). Through various initiatives such as the promotion of Medicare Advantage plans, CMS, in partnership with private insurance companies, implements payment innovation as one means of addressing the high costs of healthcare financing and delivery.

Private insurers have participated in the Medicare program since 1966. However, it was not until the Social Security amendments in 1972 that any insurer entered into an RB contract with Medicare (Patel & Guterman, 2017). In 1982, the Tax Equity and Fiscal Responsibility Act set the stage for capitated payments from Medicare to MAOs, serving as an early impetus for MAOs to introduce RB arrangements to their network providers.

Interest in Medicare Advantage plans has grown significantly since its introduction in the early 1980s. In contrast to Traditional Medicare, in many cases, Medicare Advantage offers expanded benefits schedules for those who elect to obtain coverage from such plans. The expanded benefits incentivize Medicare-eligible members to switch from Traditional Medicare coverage to Medicare Advantage plans. In 2018, approximately twenty million persons enrolled in Medicare Advantage plans, representing about one-third of all Medicare beneficiaries (Kaiser Family Foundation 2018). See Exhibit 2 for Medicare enrollment from 1999 to 2018 (with the number of beneficiaries enrolled on the left scale, and the percentage of total Medicare enrollment in an MA plan on the right scale). The enrollment trend since 2004 indicates an increasing preference for Medicare Advantage, given its fifteen consecutive annual increases in enrollment. Consequently, research into the nature of the relationships between MAOs and providers (such as PCPs), and the characteristics of the patients served, is of increasing relevance and importance.

Exhibit 2. Medicare Advantage 20-year Enrollment Trend



Source: Kaiser Family Foundation, 2018

Some MAOs enter into contracts with PCP groups that voluntarily accept up to 100% of the medical cost risk attributable to the beneficiaries assigned to them. This arrangement contrasts with the traditional reimbursement methodology, whereby physicians receive a predetermined FFS payment. In Missouri, we are aware of the existence of RB contracts as early as 1995, when local health systems and medical groups first engaged in such arrangements with MAOs (Deaconess, 1995). The current level of financial risk borne by physician groups varies with its contracts. We know of one current arrangement whereby a PCP network has responsibility for up to 80% of the total medical expenses of its attributed beneficiaries, as driven by the insurance benefit schedule.

Given the growing Medicare population and CMS' effort to steer beneficiaries into Medicare Advantage plans, we believe it is vitally important to understand the implications of assigning medical care responsibilities to MAOs and their providers, both of whom assume financial risk in this healthcare delivery model. Further, we also believe it is critical to acknowledge the presence of the beneficiaries' attributes, their access to hospitals and doctors, and their Medicare plan choices as potentially relevant factors for assessing service utilization within the Medicare program.

We wish to note that in CMS literature, Medicare Advantage plans sometimes are called Health Maintenance Organizations (HMO). CMS' use of the HMO moniker is somewhat of a misnomer (as reported by CMS) because Medicare Advantage plans can be HMOs, preferred provider organizations (PPOs), exclusive provider organizations (EPOs), special needs plans (SNP), and other plan types. Nevertheless, in this study, we follow CMS practice in their data processing and refer to any Medicare Advantage plan as an HMO plan. We also refer to the Traditional Medicare plan as the FFS plan.

Chapter 2: Literature Review

For this study, we investigate the effects of several Medicare beneficiary characteristics on plan selection and utilization. In this chapter, we offer some background information that underscores the importance of this study, discuss our choice of explanatory variable selections, and present a theoretical underpinning for our investigation. We conclude with a discussion of a previous study that we contrast with our own.

2.1 Services Utilization

Our literature search uncovered various articles describing the need to re-design or re-align healthcare organizations to move away from traditional FFS reimbursement. Generally, value-based alternatives, such as requiring healthcare providers to assume a degree of financial risk based on patient care outcomes, are advocated. Some literature cites health systems' contractual or employment schemes and insurance company mandates that attempt to modify physician behavior to yield a more value-oriented clinical practice of medicine. Examples of these types of administrative initiatives include compensation linked to performance (rather than volume); pre-authorization of patient referrals to specialists and facilities; implementation of pharmaceutical formularies; third-party oversight and intervention of pre-specified patient care activities; and publication of physicians' clinical performances These efforts to slow the growth of Medicare spending "more generally, have had limited success, and gaps in the quality of care remain" (Fisher et al., 2009).

Some research emphasizes the emerging importance of recruiting and organizing an educated and engaged core of primary care physicians to drive desired changes inherent in value-based reimbursement structures. These physicians will play the most critical role in clinically integrated networks as primary team leaders making the transition to accountable care and population health management (Floyd, 2014). However, existing literature appears to fall short in describing precisely what incentivizes PCPs to become educated and engaged in such structures, and more importantly, why they might choose, perhaps be compelled, to do so voluntarily.

2.2 Demographics

Age, gender, race, and level of education and wealth are variables frequently examined in studies of all types. These data are captured by various means such as census-taking, market research, and surveys. In healthcare-based research, patient health status is an often-used variable, with the Charlson Co-morbidity scores frequently cited as a measure of health. Here we present some preliminary background information about the variables used in this study. Additional information appears in Chapter 4.

CMS deems a beneficiary's health status as an essential consideration when determining capitation payments to MAOs. Conceptually, a healthier beneficiary requires fewer healthcare services, and a beneficiary with several diseases, also called co-morbidities, requires more services. To calibrate each capitation payment to reflect each beneficiary's health status, CMS devised a risk adjustment score (RAS) as an essential mechanism built into the capitation payment calculation. These risk scores "are calculated by statistical analysis of diagnoses and expenditures for 'fee-for-service' patients" (American Action Forum, 2015). This results in MAOs receiving less capitation for patients with fewer health risks (i.e., lower RAS score) and more capitation for patients with more significant health risks (i.e., higher RAS score).

Unfortunately, CMS has not released to researchers the individual beneficiary RAS scores for 2016. As a proxy, we incorporate a version of the Charlson Co-morbidity Index (CCMI) as an alternative means to quantify the health status of a beneficiary. We identified several studies (e.g., Sundararajan, Henderson, Perry, Muggivan, Quan, & Ghali, 2004; Bottle & Aylin, 2011; Austin, Wong, Uzzo, Beck, & Egleston, 2015) validating the use of CCMI as a means for defining patient health status by predicting the patient's one-year mortality rates. Moreover, a critical review of various scoring methods conducted by Groot, Beckerman, Lankhorst, and Bouter (2003) offers a compelling argument that CCMI is one of the more reliable means for measuring comorbidity and, therefore, is sufficient for research purposes. Other methodologies (e.g., Kaplan, Elixhauser) for determining patient health status are available, but given the general acceptance of CCMI as reported by the researchers mentioned above, and the relative ease of applying CCMI algorithms to our data, we chose CCMI as the best option. The CCMI score is the variable that allows us to account for the effect of the beneficiary's health status on their healthcare services utilization.

The CMS RAS, and by extension, the CCMI, are not without controversy. Reports suggest that MAOs (and their contracted healthcare providers) more comprehensively report the patient diagnosis codes than do FFS providers. For example, in its March 2018 report to Congress, the Medicare Payment Advisory Commissions (MedPAC), a federal agency that advises Congress on Medicare matters, states that 2016 data show that Medicare Advantage beneficiaries' RAS results were 8% higher than those of comparable Traditional Medicare beneficiaries. Consequently, Congress now requires CMS to apply annual downward adjustments to Medicare Advantage capitation payments to account for the differences in coding patterns submitted by providers. From 2010 through 2018, this downward adjustment is created by applying an annual coding intensity adjustment factor ranging from -3.41% to -5.91% (Better Medicare Alliance, 2017) to reduce the Medicare Advantage coding results to be more in line with Traditional Medicare results for comparable patients. Meanwhile, efforts are underway by CMS to continuously improve the RAS formula (and its application to the capitation payment formula), including the solicitation of input from industry stakeholders (CMS, 2018).

Given the importance of defining a beneficiary's health status in the forecasting of service utilization (and capitation payments), and in the absence of RAS scores in our CMS files, we embrace the CCMI alternative. Our careful construction of a CCMI score for each service category for each beneficiary, we believe, offers a sound methodology that produces a reasonable surrogate for the unpublished RAS data.

2.3 Access to Doctors and Hospitals

CMS considers the effects of healthcare provider availability in each county when considering whether to approve an MAO's application to operate in a county (CMS HDS, 2016). In any such application, an MAO must demonstrate that its provider network provides reasonable distance and drive time access for at least 90% of the beneficiaries residing in the county. However, exceptions can be granted and, therefore, provider availability may be differently defined in various regions. Consequently, we believe that healthcare service utilization likely is impacted by the presence or non-presence of healthcare providers and the beneficiaries' ability to access them. In this study, we include hospital proximity and physician counts for each county as variables to account for beneficiaries' access to healthcare providers.

2.4 Financial Barriers

Some research focuses on a Medicare beneficiary's ability to access medical care (Kurichi et al., 2017). Barriers to care may affect a beneficiary's utilization of services, thus impacting the medical outcomes. Among their findings, Kurichi et al. found a significant relationship between a Medicare beneficiary's financial resources and their ability to obtain healthcare services. They also found that financial resources are strongly related to a beneficiary's decision to delay healthcare services. Accordingly, we incorporate median home value in the vicinity of the beneficiary's place of residence as a surrogate "wealth" variable representing a beneficiary's ability to pay for healthcare services.

2.5 Risk-bearing Compensation

One element of this study examines the possibility that provider compensation structures, specifically risk-bearing (RB) arrangements, affect service utilization. An RB compensation model for healthcare service payment also is known as "fee-for-value," "value-based," "risk-sharing," or "risk-based" reimbursement. Hosseinian and Carmichael (2013) offer another apt description -- "gainshare/painshare" -- in their discussion of alliances like that between CMS and its MAOs, or between an MAO and a PCP group. In RB arrangements, CMS contracts with an MAO to provide medical care insurance and overall administrative management of patients assigned to the MAO. In turn, the MAO delegates significant medical care, care management oversight, and discretionary spending authority to groups or networks of providers. In return, the providers' patient care revenue emanates from budgetary surpluses or deficits and other performance incentives (as negotiated in their contracts with the MAO) rather than the per-encounter or service-specific payments associated with traditional FFS payment schemes. Presumably, this global approach to patient care and payment yields better results for all stakeholders, including MAOs, physicians, and patients (James & Poulson, 2016).

2.6 Agency Theory

One theory particularly useful in examining the financial risk-shifting that occurs from CMS to MAOs to providers is Jensen and Meckling's Agency Theory of the Firm, sometimes referred to as Principal-Agent Theory. It helps to explain several dynamics that exist in healthcare financing and delivery environs. An agency relationship is "a contract under which one or more persons (the principal) engage another person (the agent) to perform some service on their behalf which involves delegating some decision making authority to the agent" (Jensen and Meckling, 1976, p. 308). Examples include a board of directors hiring a chief executive officer to lead a company, or a house builder contracting with a plumbing company to assist with home construction. In both cases, principals delegate authority to their agents, and agents act on behalf of principals, typically in exchange for some form of compensation. Agency Theory predicts this relationship poses potential problems such as the moral hazard of the agent's self-interest, the agent's unwillingness to assume the same level of risk that the principal is willing to accept, and the problem of asymmetric information. Asymmetric information is any data, communication, or knowledge held by one party that is not immediately available to the other. Agency Theory proposes that these types of problems potentially represent inefficiencies and costs and, therefore, efforts to minimize or mitigate them should be addressed in the principal-agent contractual arrangement. Gormey and Matsa (2016) support such a viewpoint in discussing agency theory and managerial preferences.

When considering the problems posed by Agency Theory, researchers might find it is useful to understand how agreements among CMS, MAOs, and provider groups are sustainable. That understanding is an essential element of this research. Health plans, provider groups, and individual providers will seek or attract various populations, and the attributes of those populations potentially relate to plan choice and service utilization. Therefore, we begin with an examination of the healthcare financing and delivery continuum.

Conrad (1999) offered an early but somewhat rudimentary depiction of the hierarchy of healthcare risks and costs (see Exhibit 3). We interpret this model as follows. “The Health Plan” represents an MAO. “The Provider Network/Intermediary” represents a healthcare provider network or group entering an RB contract with the MAO. “The Independent Provider Organization” equates to a legal entity such as a primary care medical practice corporation that is an owner of, or participant in, the provider network. “The Individual Primary Care Physician” is an owner or member of the medical practice corporation to which specific patients are attributed. “The Non-primary Care Specialist” is a physician to which a PCP would refer a patient for medical care that cannot be provided by the PCP.

Exhibit 3. Conrad’s Risk-bearing Hierarchy

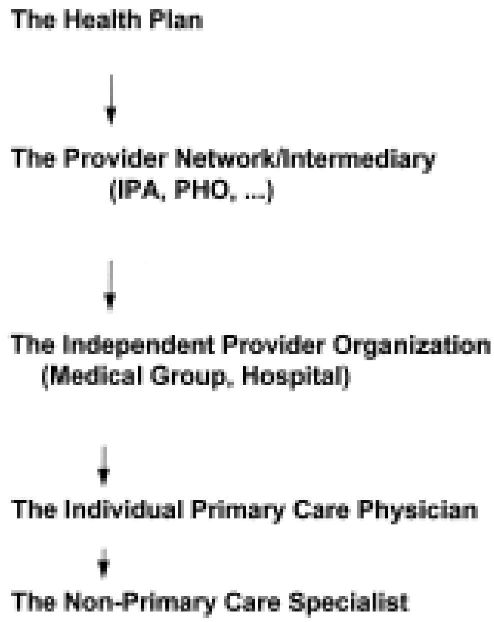


Exhibit 3. Obtained from “Risk-bearing arrangements and capital financing strategies for integrated health systems : Conceptual framework and case examples,” by D. Conrad, 1999, *The Quarterly Review of Economics and Finance*, *Volume 39*(4) Winter 1999, p. 451. Copyright 1999 by the Board of Trustees of the University of Illinois.

In Exhibit 4, we present an updated and expanded view of the RB hierarchy by defining the many principal-agent relationships within a typical Medicare Advantage plan structure. Here we display a series of cascading relationships whereby many players simultaneously perform in the role of principal and agent. From the cascade’s beginning to its end, the delegation of authority and funds dissemination diminishes with each step. Why does this model hold up? For example, it is unclear what effect, good or bad, the RB PCP compensation model has on the Medicare Advantage program. Nevertheless, we know that this compensation model has been in place for MAOs and PCPs in the St. Louis, Missouri, market for more than 20 years (Deaconess, 1995). This history raises questions. Are agency theory’s predicted problems somehow mitigated within the cascade? Is there the presence of bounded self-interest as discussed by Bosse and Phillips (2018) wherein the RB PCPs perceive their MAOs to be fair, resulting in behavior that is rewarding to both parties? Does this RB compensation model contain incentives compatible with the desired outcomes as contemplated by the Theory of Value-based Payments in Conrad's later research (2016)? Let us further examine these relationships.

Exhibit 4. The Cascading Principal-Agent Relationships of Medicare Advantage

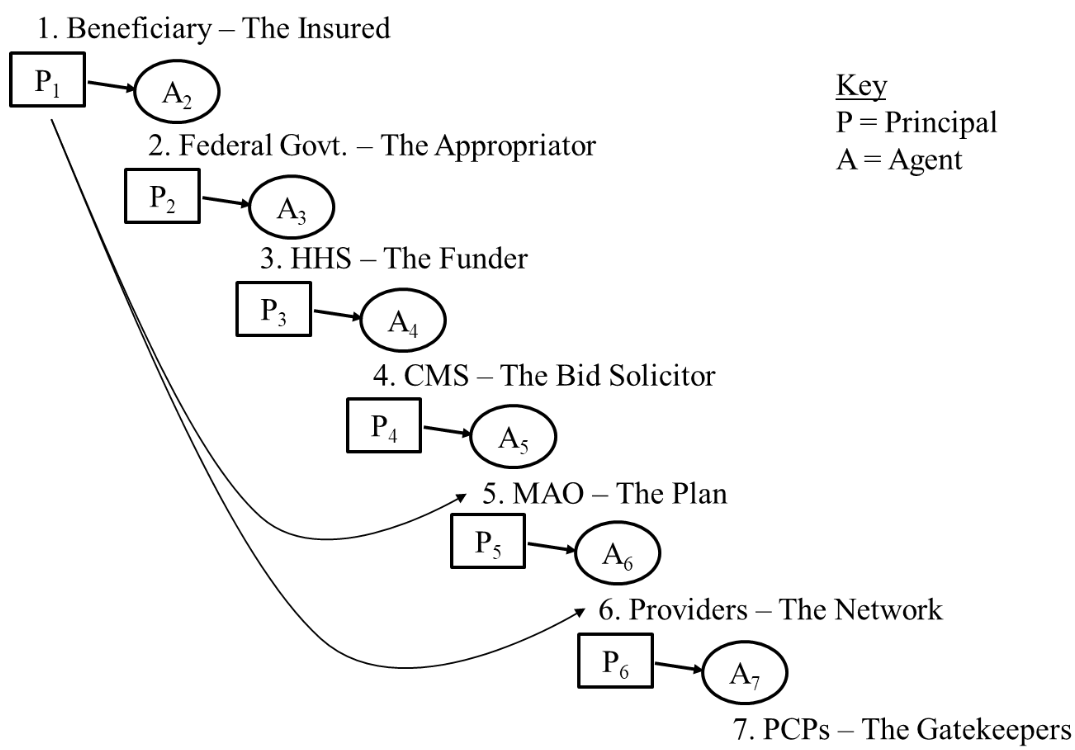


Exhibit 4. Author's creation.

P_1-A_2. The beneficiary is the insured person who relies upon the Federal Government, the agent, to provide access to Medicare medical benefits and health insurance coverage. The beneficiary pays for these services via federal income tax dollars and Medicare Part B premiums to the Federal Government's Internal Revenue Service.

P_2-A_3. The Federal Government assumes the role of the principal as it delegates the benefits and insurance coverage responsibility to its agent, HHS. HHS receives funding via an appropriation in the annual federal budgeting process.

P_3-A_4. HHS assumes the role of the principal as it delegates the benefits and insurance coverage responsibility to its agent, CMS, a unit of HHS. CMS receives funding via general revenue, payroll taxes, and beneficiary premium payments, all of which are collected by the federal government.

P_4-A_5. CMS becomes a principal as it delegates some of its responsibilities to its agents, the private health insurance companies approved by the Medicare Advantage program. These insurance companies are called Medicare Advantage Organizations (MAOs). They receive a monthly capitation payment for each beneficiary insured in their plan. The payment amounts derive from a multi-faceted methodology that incorporates various factors such as a bidding process, patients' health statuses, average annual costs of care, and geographical locations.

P_5-A_6. The MAO, in the role of principal, delegates medical care responsibilities to their agents, the provider networks that enter into various payment arrangements, including RB compensation, with the MAOs. A provider network can take many forms, such as a contracting group representing several primary care medical practices, or a large, clinically integrated network comprising entities such as hospitals, outpatient facilities, medical practices, and ancillary service providers.

P_6-A_7. The provider network, as principal, engages PCPs as its agents, either through sub-contracts or employment. Many MAOs require the beneficiary to select a provider network PCP as their medical gatekeeper. The PCP directly or indirectly (via the provider network) receives payments from up to five sources: the patient (from deductibles, co-payments, and fee-based services); a monthly capitation payment; a share of the surplus (or deficit) from the medical budget; and various outcomes incentive payments from the MAO.

Other relationships after A_7. PCP gatekeepers, as principals, refer patients to other providers, their agents, as appropriate, with those provider payments assessed against the RB budgets. These referrals typically occur when the patient's medical needs are beyond the clinical competency of the PCP or the service capabilities within the PCP's medical practice. It is from these referral and payment arrangements that the RB model of compensation occurs. We shall later describe the specifics of this arrangement. Downstream providers may engage other providers (e.g., hospitals contracting with emergency medicine physicians for coverage in the emergency department) and so on. These principal-agent relationships continue along the healthcare continuum until the patient's medical needs are satisfied.

Also, we note two other principal-agent associations. First is the beneficiary's selection of the MAO to provide a selection of Medicare Advantage plans that include access to provider networks. Second is the beneficiary's selection of a PCP gatekeeper (typically required by the MAO plan). In both cases, the beneficiary is the principal delegating authority and facilitating funding to its agents.

It is this cascade of relationships from the beneficiary to the final healthcare provider on the medical care continuum that demonstrates a robust presence of principal-agent arrangements in the MA industry. We believe this business environment supports our selection of Agency Theory as the context for this research.

Eisenhardt's Agency Theory Overview offers additional support to our theoretical approach. In our view, each of the seven elements described in her overview applies to the MAO/PCP arrangement. In Exhibit 5, we offer our application for each of Eisenhardt's constructs as they relate to the MAO/PCP relationship.

Exhibit 5. Eisenhardt's Agency Theory Overview

Element	Eisenhardt's Constructs	Our Application to the MAO/PCP Relationship
Key Idea	Principal-agent relationships should reflect efficient organization of information and risk-bearing costs.	Information exchange is encouraged by both parties as they seek to minimize risk, reduce the cost of care, and optimize financial performance. Much information exchange occurs during joint conferences and via website portals. The MAO and PCP share the enrollee's medical costs via mutual agreement.
Unit of Analysis	Contract between principal and agent	There is a formal agreement signed by the MAO and PCP.
Human assumptions	Self-interest Bounded rationality Risk aversion	An MAO's contractual agreement with the PCP imposes terms, conditions, incentives, and compromises designed to address PCP's self-interests, bounded rationality, and risk aversion.
Organization assumptions	Partial goal conflict among participants Efficiency as the effectiveness criterion Information asymmetry between principal and agent	An MAO typically is a large corporation with abundant resources, formal processes, and a structured hierarchy. A PCP generally operates in a smaller, autonomous environment with limited resources. Cultural and operational differences likely exist.
Information assumption	Information as a purchasable commodity	MAOs and providers can invest in technology and human resources to capture and exchange information. Both seek timely information capture and exchange. MAOs also invest in monitoring activities to ensure adequate information capture.
Contracting problems	Agency (moral hazard and adverse selection) Risk sharing	MAOs and PCPs attempt to address these concerns through prolonged contract negotiations, complex terms and conditions, and risk-sharing formulas designed to drive the intended behaviors and outcomes.
Problem domain	Relationships in which the principal and agent have partly differing goals and risk preferences (e.g., compensation, regulation, leadership, impression management, whistle-blowing, vertical integration, transfer pricing)	The MAO desires for the PCPs to undertake every possible action to optimize each enrollee's health while minimizing costs. The PCPs have multiple patients, busy practices, multiple payer agreements with MAOs, and limited resources. Goal conflicts, inefficiencies, and information exchange challenges are inevitable. It is through contract terms and information exchange that the parties seek to engage productively with one another.

Exhibit 5: Adapted from "Agency Theory: An Assessment and Review," by Kathleen M. Eisenhardt, 1989, *The Academy of Management Review 14*(1), p. 59. Copyright 1989 by the Academy of Management.

To further validate our selection of Agency Theory as the context for this study, we found several examples of researchers incorporating Agency Theory into their works related to healthcare subject matter. Schneider & Mathios (2006) use the principal-agent framework in their study of healthcare utilization and the associated monitoring costs incurred by healthcare insurers. Their discussion places the insurer as the principal and the physician as the agent. A stylized model of the principal-agent relationship is proposed by Kantarevic & Kralj (2015) to investigate physician payment contracts. They identify "payers" as the principals and the physicians as the agents. Sinclair-Desgagne' & Spaeter (2017) examine incentive compensation in a "static principal-agent moral hazard setting." They identify the patient as a principal who engages the actions of a physician as their agent. Fuloria & Zenios identify principal-agent problems involving treatment intensity. Their principals are the purchasers of healthcare services, and the agents are the providers of healthcare services. Jiang, Pang, & Savin evaluate principal-agent contracting models for the allocation of outpatient capacity. In their model, purchasers of healthcare services are the principals, and healthcare providers are the agents. Each of these studies examines various aspects of predicted principal-agent problems such as asymmetric information, incentive alignment, and inefficiency. In conclusion, we find that the use of Agency Theory as a theoretical underpinning in healthcare research is not uncommon.

2.7 Other Research

Our research uncovered only one study (Landon et al. 2012) that offered a comprehensive comparison of Traditional Medicare and Medicare Advantage services utilization. The study concluded that Medicare Advantage beneficiaries utilize fewer services than those in Traditional Medicare. Like ours, that study controlled for attributes such as race/ethnicity, age, sex, residence zip code, and expected socio-economic status. Each beneficiary's race/ethnicity, age, sex, and residence zip codes were extracted from the CMS Master Beneficiary Summary Files. One of the study's two socio-economic variables was "beneficiaries age greater than 65 living below the federal poverty level." The second socio-economic variable was "urban." While there is no mention of the data sources, we surmise that the beneficiaries' residences zip codes likely were the bases for those determinations.

Because they lacked the diagnostic codes for individual Medicare Advantage patients and were unable to calculate risk adjustment scores, the researchers used data from the Medicare Consumer Assessment of Healthcare Providers and Systems surveys as a proxy for the beneficiaries' health statuses. Over several years, the surveys were conducted by mail with telephone follow-up to secure random, representative samples of the Traditional Medicare and Medicare advantage populations. The survey respondents were asked to report their general and mental health statuses using a scale of excellent to poor. This health status proxy is cited as a limitation in the study.

The study also did not consider the compensation arrangements of PCPs. The authors suggested that more research is needed to understand the management practices of Medicare Advantage plans, the plan designs, and how they relate to healthcare financing and delivery reform. Nevertheless, our literature review suggests that this was the first and perhaps only comprehensive study that compares service utilization patterns for Traditional Medicare and Medicare Advantage beneficiaries, and does so with consideration to beneficiary characteristics.

Our study contrasts with this previous research. First, we identify all major stakeholders in the Medicare program to better understand the critical players in the federal government's effort to reform healthcare and how that relates to the growth of Medicare Advantage enrollment. Second, we incorporate a theoretical basis, Agency Theory, to understand the relationships, issues, and challenges among those stakeholders. Third, from our field research and physician interviews, we describe the nature of RB compensation arrangements between MAOs and PCPs. Fourth, by calculating the CCMI score for each service category for each beneficiary using the reported diagnostic codes from patients' medical claims and encounter records, we present an improved method for defining the beneficiary's health status. Fifth, we incorporate values for hospital proximity and physician presence to control for health services availability and to assess their impact on plan choices and services utilization. Sixth, we consider the impact of various Medicare plan choices on beneficiary services utilization. Seventh, by limiting our study to a regional market, in this case, the state of Missouri, we incorporate a known RB PCP compensation arrangement (gleaned from our field research) as a variable that is useful in assessing the effect of that arrangement on service utilization. Lastly, our access to 2016 data allows us to conduct analyses based on recent information. With these enhancements, we construct an improved framework for understanding many inner workings of the Medicare program while investigating the effects of a beneficiary's attributes, Medicare plan choice, and access to providers on service utilization.

Chapter 3: Initial Research and Hypotheses

Early in this research, we undertook two initiatives. First, we conducted a limited, qualitative research project with a PCP group to better understand the research domain, especially concerning what incentivizes them to engage in RB contracts and to learn more about the nature of those contracts. As part of that experience, we attended several meetings between the group and two MAOs. In all meetings, the parties discussed performance metrics and related information. Second, we developed a model (see Appendix A for additional discussion) that simulates many of the financial elements of RB contracts that might exist between MAOs and PCPs. The following section summarizes these efforts.

3.1 Incentives for PCPs to engage in risk-bearing contracts

To enhance our domain knowledge, on four occasions during the year prior to the start of this study, we observed business meetings of Harmony IPA, LLC (Harmony), an independent physician association (IPA) operating in the St. Louis, Missouri, metropolitan area. Harmony's membership is comprised of ten Board-certified, primary care physicians. Harmony is a physician-owned, physician-led firm created for the exclusive purpose of contracting with Medicare Advantage plans and managing the care of the attributed patients. A "sub-agency" relationship exists between Harmony and each physician member who contractually agrees to accept the terms and conditions in the agreements between Harmony and the MAOs.

All members were invited to attend their business meetings (each lasted about two and a half hours), and a majority did during our presence. At these business meetings, among other agenda items, we discussed our research, their experience with risk-based compensation, and their relationships with MAOs. During three meetings, part of the agenda was devoted to discussions with representatives from MAOs, an exercise known as the Joint Operation Committee (JOC) meetings. Separately, we also conducted a semi-structured interview with each of the Harmony PCPs. The interviews were designed principally to encourage each PCP to discuss their understanding of their RB agreements, their relationships with the MAOs, and the impact of Medicare Advantage plans on their IPA, medical practices, and patients.

Harmony has about 3,000 Medicare Advantage beneficiaries attributed to them by two different MAOs, and its PCPs accept up to 80% of the medical cost risk associated with those beneficiaries. Harmony PCPs say this is because the St. Louis area was an early adopter of Medicare Advantage plans. Most Harmony PCPs, through various corporate structures, have participated in RB payment arrangements for more than 20 years. Some of the Harmony physicians spoke of their association with Deaconess Hospital and its St. Louis Medical Group dating to the early 1990s when the organization contracted with Medicare Advantage plans when they first appeared in the area. The PCPs tell us that their experience and financial success with RB agreements offer confidence and comfort to continue with those engagements.

We note that MAOs, depending on the laws in the states where they operate, may have the option of employing their medical providers or otherwise owning medical practices, rather than contracting with entities like Harmony to provide such services. In Missouri, the MAOs could do so because there is no statutory prohibition against the corporate practice of medicine ("Health care regulatory primer," 2017). From the PCPs and MAOs' representatives we have interviewed, we conclude that the MAOs in the St.

Louis area generally prefer the third party arrangement, hence the agency relationship with Harmony and other provider organizations.

Based on our interviews with Harmony physicians and witnessing their interactions with MAOs, we offer three observations. First, MAOs enter into contracts with CMS because the MAOs believe they have the expertise needed to care for a defined patient population, and can do so profitably. The two MAOs that contract with Harmony are large corporations, one with a national presence and one with a regional presence. In Missouri, these two MAOs enroll about 27% of the Medicare Advantage beneficiaries. They each have local offices staffed with dozens of professionals that include but are not limited to administrators, marketers, provider recruiters, information technologists, nurse case managers, auditors, actuaries, and clerical support staff. The MAO representatives stated that the St. Louis-area operations are among the most profitable in their companies.

Second, the Harmony PCPs report there are significant financial incentives to manage aggressively the overall cost of care for the Medicare Advantage patients assigned to them. Consequently, they must proactively monitor patient care activity both inside and outside of their medical practices. For example, they insist that facilities and specialists to whom they refer patients provide regular updates or reports that inform each patient’s status. Another example is the importance of timely communications from hospital emergency department physicians who attend to the PCPs’ patients. In both cases, they expect to participate in the care management planning for their patients to avoid duplicative testing, clinically unnecessary procedures, and unmanaged referrals. During their interviews, several Harmony PCPs told us that they believe their care management techniques carry over to their Traditional Medicare patients. They have adopted these disciplines as part of their ordinary office operations even though the financial rewards are significantly less. Third, within a PCP's medical practice, a PCP will have a more exceptional ability to manage the overall cost of care for Medicare Advantage patients than their Traditional Medicare patients because they (PCPs) receive informational and operational support from the MAOs. This type of support includes the MAO's provision of a website portal where PCPs and their staff can access timely clinical and financial information about their attributed patients. Other examples include but are not limited to: a) assistance with on-site medical record audits and documentation to assure that procedure and diagnostic codes are adequately documented, b) MAO-generated prompts that remind PCPs and their staff to encourage patients to schedule appointments for routine care such as annual physical exams or specialized care such as eye examinations for diabetic patients, c) identification of patient care opportunities that lead to improved financial results and d) access to price information that is useful when considering where to refer patients. They do not receive this same level of support from the Traditional Medicare program because there is not an administrative infrastructure in place to do so.

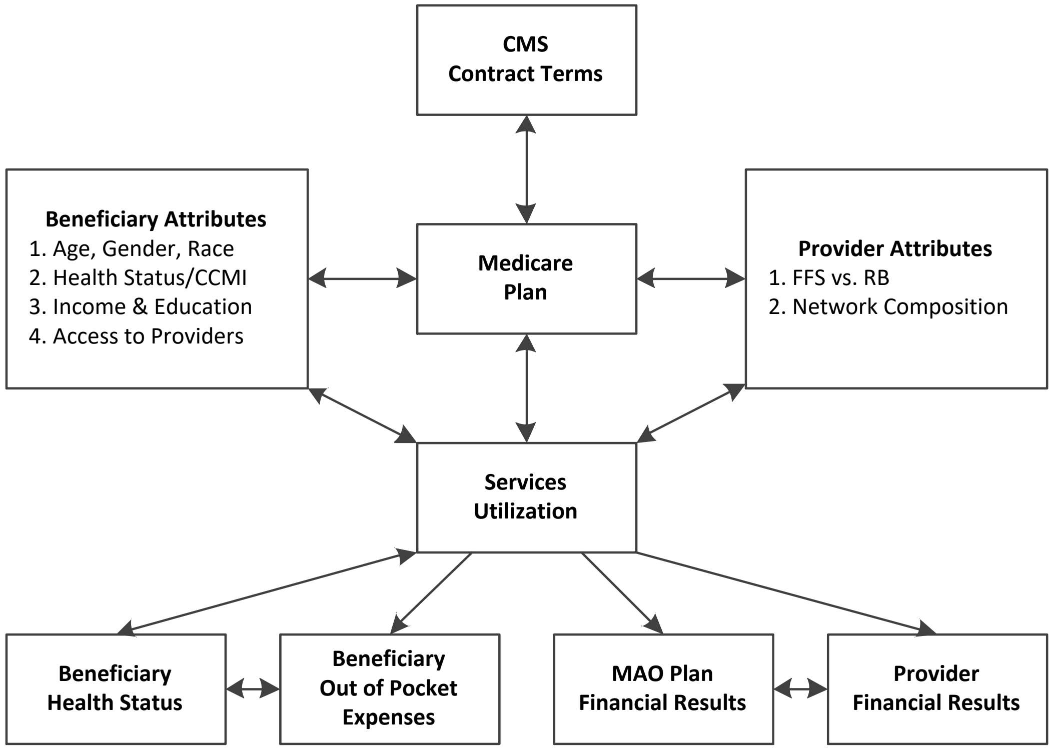
Related to PCP care management activity, including referral patterns and communication with other providers, is the composition of an MAO's provider network. CMS guidelines state:

> "CMS requires that organizations contract with a sufficient number of providers and facilities to ensure that at least 90 percent of enrollees within a county can access care within specific travel time and distance maximums" (cms.gov, 2017)."

CMS' health service delivery manual entitled "CY2016 MA HSD Provider and Facility Specialties and Network Adequacy Criteria Guidance" describes expectations for the minimum number of doctors, hospitals, and other service providers that must be present in each county of the MAO's plan coverage area. Those expectations are based on county type. There are five county types: a) Large Metro, b) Metro, c) Micro, d) Rural and e) Counties with Extreme Access. Doctor coverage, for example, also includes requirements for each of several specialties. Other service requirements may be defined as programs, provider affiliations, or facilities. Each minimum coverage requirement generally is stated as a ratio per 1,000 beneficiaries residing in a county. For example, CMS set a standard of 12.2 inpatient hospital beds per 1,000 beneficiaries in a county. MAOs make these various calculations when submitting their plan applications to CMS. They also must submit justifications for any guideline exceptions. According to CMS, some exceptions are allowed. Consequently, the composition of provider networks may differ among MAO plans, and provider access may vary by county within a plan coverage area. Therefore, we conclude that an MAO's plan profile is shaped, in part, by its provider network, and that affects a beneficiary's access to and use of doctors and hospitals.

From our research, fieldwork, contract reviews, and industry experience, we propose in Exhibit 6, a conceptual design of the relationships and processes existing among the players in this environment. It also demonstrates how those relationships affect patient health status, services utilization, and financial outcomes (note: the author is a healthcare administrator with thirty-five years' experience that includes negotiating several Medicare Advantage agreements between insurers and providers).

Exhibit 6. Significant Factors in the Medicare Advantage System

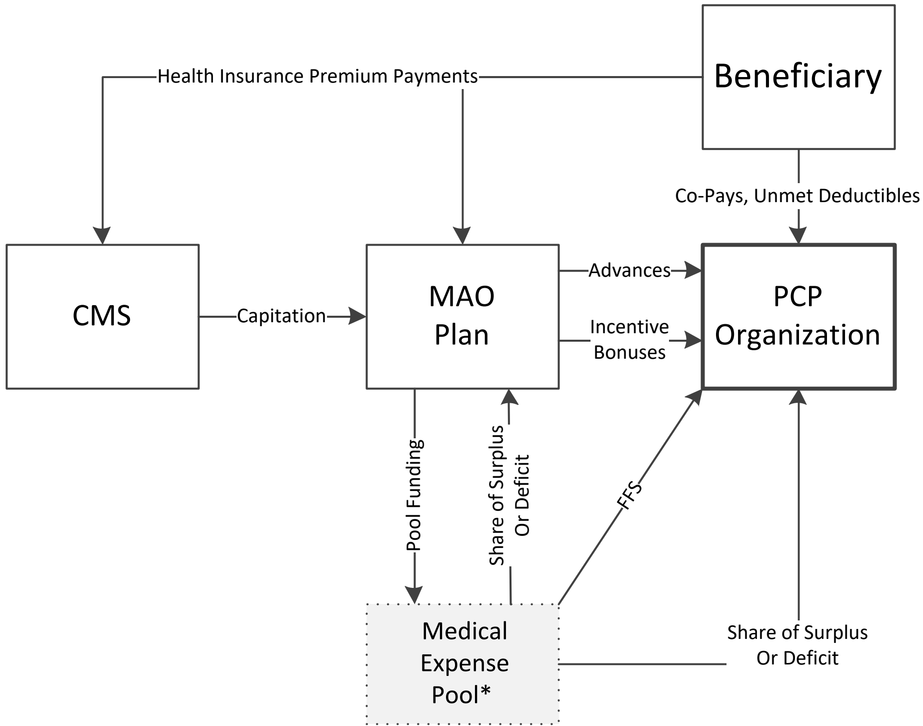


The boxes in Exhibit 6 diagram indicate factors in the healthcare financing and delivery environment that affect Medicare Advantage stakeholders. The initiating party, CMS, supplies contract terms and conditions that define the various Medicare plan choices. The CMS contract terms influence the MAO's plan contracts with the beneficiaries and providers recruited by the MAO for participation in its plan. The characteristics of the beneficiary, plan, and PCPs influence the process by which PCPs render healthcare services (including mix and quantity) to each beneficiary. The mix and quantity of services consumed by the beneficiary influence the beneficiary's health status and potentially drive successive service utilization events. Service utilization also impacts the beneficiary's out-of-pocket costs, the MAO's financial results, and the compensation paid to PCPs, all of which are related to the contract terms first initiated in the process. The process concludes with reconciled payments from the MAO to PCP. This basic diagram is useful in exposing the various financial risks assumed by the parties.

3.2 Financial Risk Models

Our understanding of financial risk comes from a review of current service agreements between Harmony and two MAOs. The definition is also informed by previous payer-provider negotiations experience. The contract language within these agreements, combined with Harmony's internal risk-assignment protocols, reveals numerous and complex terms whereby the PCPs collectively and individually incur financial risk. We also discovered that these contracts contain confidentiality statements that prohibit public and private disclosure (even for research purposes) of the specific terms and conditions, the MAOs' proprietary information, and Harmony's financial performance resulting from the contracts. Nevertheless, from our interviews with Harmony participants, our contract reviews, our fieldwork, and our thirty-five years' healthcare administration experience, we can extract distinctive features of these types of agreements. These features reveal representative components of the compensation paid to RB PCPs that care for Medicare beneficiaries. In Exhibit 7, we display a prototypical model that incorporates several of these features. Also, see Appendix A for more discussion of PCP RB compensation arrangements with MAOs.

Exhibit 7. Author’s Depiction of RB Funds Flow



*For payment of services provided by Physicians (PCPs and Specialists), Hospitals and Other Facilities, Ancillary Service Providers, Durable Medical Equipment, Home Healthcare, Pharmacies, Re-insurance Premiums, Etc.

In Exhibit 7, the solid boxes represent the stakeholders, the arrows represent the flow of dollars, and the shaded box represents the pool of funds available to pay the beneficiary’s medical costs. The model demonstrates how the PCP organization may generate revenue from any of five sources: a) MAO’s advances, b) MAO bonus payments, c) FFS payments, d) share of surplus or deficit, and e) beneficiary co-payments or unmet deductible obligations. Financial risk resides with the Medical Expense Pool.

The complexity of the model is due to various contractual terms that incorporate several pages of definitions, formulas, and inter-related payment methods that collectively determine the PCPs’ compensation. For example, an MAO-PCP contract may include advance capitation payments that must be return in full or part if the medical pool reconciles to a deficit position. Another example concerns the percentage share of a pool surplus. The PCP's share may be determined, in part, by the achievement or non-achievement of benchmarks for clinical outcomes or service utilization. These types of post-service delivery arrangements can materially affect the amount of financial risk assumed by the PCP. Consequently, the RB funds flow model is much more complicated than the FFS model (see Exhibit 8), whereby PCPs generate revenue from any of three sources: a) FFS payments, b) incentive bonuses, and c) beneficiary co-payments or unmet deductible obligations.

Exhibit 8. Author's Depiction of FFS Funds Flow

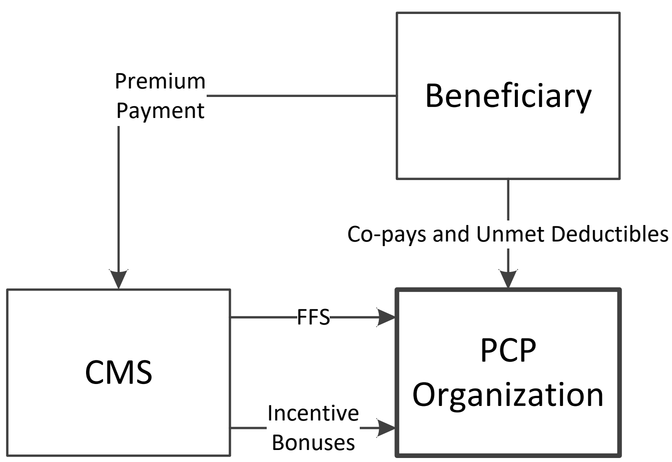


Table 1 contrasts these two forms of payment (RB and FFS). The dollar amounts and quantities of services shown are hypothetical, but they reasonably approximate actual data. Let us assume that CMS actuaries have determined that a specific patient is allotted an annual budget of $10,000, the anticipated cost of all covered benefits, for the upcoming calendar year. This amount stems from an algorithm based on several factors, such as the patient's gender, age, health status, and place of residence, as well as the average historical cost of care demographically comparable Medicare patients. In the FFS program, a patient may see a PCP four times per calendar year. In this illustration, the payment from CMS to the PCP averages $120 per visit, totaling $480 annually (4 visits at $120 each) and leaving a balance of $9,520 for payments to other healthcare services. The $480 total payments equate to an average of about $40 per month. If more than $10,000 of budgeted costs are incurred in this calendar year, CMS incurs them. If less than the budgeted costs are incurred in the calendar year, CMS retains the unspent funds.

In the RB model, the calendar year budget is paid in monthly installments by CMS to the MAO for each beneficiary enrolled with the MAO. In this illustration, the annual payment for one specific patient is $10,000. The MAO typically retains a portion of the budget, say 15%, to cover its operating costs, to pay for some specialized services for the patients, to establish reserves for unexpected losses, and, presumably, to capture a profit. The PCP group may or may not receive from the MAO any direct payments for services rendered to the patient. Any direct payments are defined by the contract terms between the PCP group and the MAO. In this illustration, a PCP group member assigned as the patient's medical gatekeeper aggressively manages the patient's care, offers abundant services in the primary care setting, and limits patient referrals to only the most efficient and effective healthcare providers outside the PCP's medical practice location. As a result, the total amount paid to all providers is $6,500 for the calendar year. That amount, added to the $1,500 MAO's retention, totals $8,000, leaving a $2,000 surplus. In this hypothetical contract between the MAO and the PCP group, the MAO apportions

80% of the surplus (or deficit) to the PCP group. In this case, the $2,000 annual surplus yields a $1,600 total annual payment to the group, for a monthly average of $133 for this one patient. The distribution of the surplus within the group is a function of contractual payment arrangements agreed upon by the group's members. The balance of the surplus is retained by the MAO, which, in this case, is $400 annually or about $33 per month.

Table 1

FFS vs. RB Compensation Illustration
(Dollars except as otherwise indicated)

	Fee-for-Service	Risk-bearing
Patient's Annual Budget	10,000	10,000
MAO Retention	n/a	1,500
PCP FFS Payments	480	0
Other Provider Payments	9,520	6,500
Total	10,000	8,000
Net Surplus/Deficit	0	2,000
PCP Share of Surplus/Deficit	n/a	80%
PCP Earnings	n/a	1,600
PCP Average Earnings per Month	40	133

Note: n/a = not applicable

By comparing the average monthly earnings for the two scenarios, one observes that the RB PCP earns approximately three times the FFS arrangement. To put this in further perspective, we reviewed actual data indicating that Harmony PCPs averaged more than $170 per member (beneficiary) per month for fourteen years with one of the MAOs. For example, a Harmony physician having 100 patients in this plan would realize annual revenue of approximately $204,000 (100 patients x $170/month x 12 months) based on this MAO's contract with Harmony. Furthermore, this revenue (i.e., $204,000) is in addition to earnings received from the other patients in the medical practice. This level of financial success suggests that the principal-agent relationship, and corresponding contract, must be mutually beneficial because both parties continue in a similar contractual relationship today. Furthermore, it suggests the contract terms and the parties' relationship with one another mitigates problems predicted by agency theory.

3.3 Hypotheses

We formulate the following hypotheses based on the collective insights gleaned from our literature review, fieldwork, contract reviews, funds flow models, and compensation comparisons.

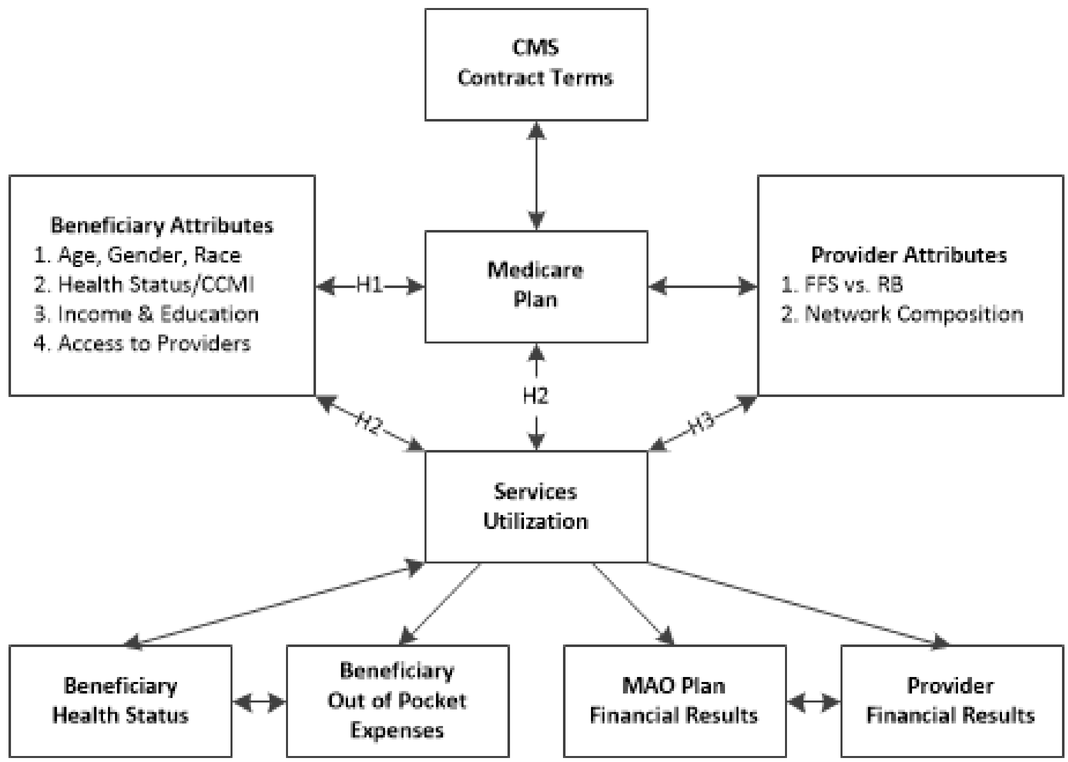
Hypothesis 1. We expect that a beneficiary's traits of age, gender, race, and health status (as defined by their CCMI score) will have statistical relevance to the Medicare plan choice. Also, we expect a beneficiary's access to medical care (as defined by their proximity to hospitals and the number of doctors in their county) is a significant factor in plan choice. Further, it is believed that a beneficiary's presumed income and educational attainment, as determined by their residence zip code and county, are additional factors that also affect plan choice. Accordingly, we state H1: Medicare plan choice is statistically related to a beneficiary's traits, access to healthcare, and presumed levels of income and education.

Hypothesis 2. Medical services received by Medicare beneficiaries will vary according to beneficiary characteristics, access to medical care in their county of residence, the demographic characteristics of individuals who reside in the same Postal Zip code, and the choice of Medicare plans. Therefore, we propose H2: A beneficiary's traits, access to healthcare, presumed levels of income and education, and Medicare plan choice collectively are statistically related to service utilization.

Hypothesis 3. RB PCPs pro-actively engage in medical care and care management activity designed for efficient care delivery both inside and outside their medical practice locations. They also receive operational support from the MAO's with whom they have contracts. Accordingly, we state H3 as follows: Beneficiaries of HMO plans that contract with RB PCPs as medical gatekeepers use fewer healthcare services than do beneficiaries of other plans, and those differences are statistically significant.

In Exhibit 9, we insert these hypotheses into the significant factors model to demonstrate their presence in the model.

Exhibit 9. Hypotheses within the Significant Factors Model



To summarize, we predict that beneficiary personal attributes, access to doctors and hospitals, and presumed levels of income and education all are statistically relevant to Medicare plan choices (H1). Furthermore, we predict that the explanatory variables in H1, along with Medicare plan choice, are statistically related to service utilization (H2). We also expect that the presence of RB PCPs results in fewer, per-beneficiary services utilization as compared to the FFS model (H3). Operationally, we propose that these significant factors have downstream implications, namely the beneficiary's ongoing health status and the stakeholders' financial results.

Chapter 4: Methods

This research requires an in-depth understanding of the Medicare system and the technical data contained in the research files. There are dozens of Medicare plan options, hundreds of unique variables, and tens of thousands of standardized diagnosis and procedure codes. Some of the data describe each beneficiary's attributes, insurance plan, and the schedule of benefits received from their insurance plans. Other data describe the disease diagnoses, medical procedures, the places of those procedures, and incurred costs attributable to each beneficiary. There are numerous instructions, data dictionaries, and record layout files, both public and private, compiled to guide researchers in the proper use and interpretation of these data. Also, the research data have some limitations that, if ignored, might result in spurious conclusions from statistical analysis. In this chapter, we offer an overview of many of the essential data elements that compose the Medicare research files. We also discuss the approach for our study.

4.1 Medicare Data

CMS produces more than fifty archival data files for use in research. It contracts with a third party to operate the Research Data Assistance Center (ResDAC), a resource agency designed to assist researchers in facilitating requests for research data and interpreting that data. ResDAC, located at the University of Minnesota in Minneapolis, is staffed by faculty and staff to assist researchers with their CMS-related projects. The FFS data are derived from insurance claims processed by CMS third-party contractors, and the HMO data come from encounter data reported by MAOs. All data are stored in and retrieved from CMS' data repository called the Chronic Conditions Warehouse. Researchers may access the data via an interactive, online capability made available by CMS. Alternatively, a researcher may request to purchase the data placed on an external storage medium shipped to the researcher -- the method selected for this study.

The CMS file structure complexities, and the quantity of data elements contained therein, can be daunting to researchers. Fortunately, ResDAC also offers an instructional website and annually hosts several workshops to educate researchers. We attended two of the multi-day workshops. One workshop focused on using Traditional Medicare data and the other on the use of Medicare Advantage data. The information disseminated at these workshops, coupled with the staff's technical guidance, was instrumental in our successful application and receipt of Medicare research data.

4.2 Medicare Codes

CMS utilizes various coding systems in its administration of health insurance benefits programs, including the Medicare programs. Coding is integral to administering both Traditional Medicare and Medicare Advantage programs because it is the basis for reporting types and volumes of services rendered by healthcare providers. Further, the research data from CMS incorporates the entirety of each coding system. Because we organize some of the research data using standard grouping conventions and apply those conventions to the development of some variables, it is essential to provide an overview of these coding systems.

4.2.1 ICD Diagnosis codes. The World Health Organization (WHO) is responsible for defining and continuously updating a code set known as the International Classification of Diseases (ICD). According to WHO, the

> "ICD is the foundation for the identification of health trends and statistics globally, and the international standard for reporting diseases and health conditions. It is the diagnostic classification standard for all clinical and research purposes. ICD defines the universe of diseases, disorders, injuries and other related health conditions, listed in a comprehensive, hierarchical fashion …"

Virtually every hospital, outpatient, and physician encounter record within CMS' massive data warehouse contains one or more ICD codes representing the injuries and diseases experienced by each beneficiary.

In the third quarter of 2015, the ICD codes underwent a significant revision that expanded the number of codes from about 14,000 codes (identified as the ICD 9th revision or ICD-9) to approximately 68,000 codes and sub-codes (identified as the ICD 10th revision or ICD-10). Consequently, in 2015 and 2016, some CMS records contain both ICD-9 codes and ICD-10 codes. Fortunately, the codes can be placed into general groupings that allow researchers to aggregate the individual codes into logical categories (see Table 2). Also, because ICD-9 codes and ICD-10 codes contain different prefixes, we can identify codes from either version.

Table 2

International Classification of Diseases (ICD) Versions 9 & 10

Version 9	Version 10	Description
001-139	A00-B99	Infectious and Parasitic Diseases
140-239	C00-D49	Neoplasms
240-279	E00-E89	Endocrine, Nutritional and Metabolic Diseases, and Immunity Disorders
280-289	D50-D89	Diseases of the Blood and Blood-Forming Organs
290-319	F01-F99	Mental Disorders
320-389	G00-H95	Diseases of the Nervous System and Sense Organs
390-459	I00-I99	Diseases of the Circulatory System
460-519	J00-J99	Diseases of the Respiratory System
520-579	K00-K95	Diseases of the Digestive System
580-629	N00-N99	Diseases of the Genitourinary System
630-677	O00-O9A	Complications of Pregnancy, Childbirth, and the Puerperium
680-709	L00-L99	Diseases of the Skin and Subcutaneous Tissue
710-739	M00-M99	Diseases of the Musculoskeletal System and Connective Tissue
740-759	Q00-Q99	Congenital Anomalies
760-779	P00-P96	Certain Conditions Originating in the Perinatal Period
780-799	R00-R99	Symptoms, Signs, and Ill-Defined Conditions
800-999	S00-T88	Injury and Poisoning
V01-V86	Z00-Z99	Supplementary Classification of Factors Influencing Health Status and Contact with Health Services
E800-E999	V00-Y99	Supplementary Classification of External Causes of Injury and Poisoning

Note: Adapted from ICD-10-CM, International Classification of Diseases, 9th & 10th Revisions, p. vi. Copyright 2014 by Practice Management Information Corporation.

4.2.2 ICD Procedure codes. Related to the ICD-9 and ICD-10 diagnostic codes are the ICD-9 and ICD-10 procedure codes. The Health Insurance Portability and Accountability Act of 1996 (HIPAA) mandated that providers submit these procedure codes on all <u>inpatient</u> medical claims submitted to Medicare (American Hospital Association, 2009). In the Medicare programs, there are no other required uses of these codes. ICD-9 procedure codes are identified as Volume 3 codes and contain three to four digits (including two decimals). There are approximately 3,800 such codes. ICD-10 procedure codes are identified as Procedure Coding System (PCS) codes and contain seven alpha-numeric characters. There are more than 70,000 ICD-10 PCS codes. Tables 3 and 4 demonstrate the code groupings from the two ICD coding systems in effect beginning in 2015.

Table 3

2015 ICD-9 Volume 3 Procedure Code Groups

Codes	Descriptions
00-00	Procedures and Interventions, Not Elsewhere Classified
01-05	Operations on the Nervous System
06-07	Operations on the Endocrine System
08-16	Operations on the Eye
17-17	Other Miscellaneous Diagnostic and Therapeutic Procedures
18-20	Operations on the Ear
21-29	Operations on the Nose, Mouth, and Pharynx
30-34	Operations on the Respiratory System
35-39	Operations on the Cardiovascular System
40-41	Operations on the Hemic and Lymphatic System
42-54	Operations on the Digestive System
55-59	Operations on the Urinary System
60-64	Operations on the Male Genital Organs
65-71	Operations on the Female Genital Organs
72-75	Obstetrical Procedures
76-84	Operations on the Musculoskeletal System
85-86	Operations on the Integumentary System
87-99	Miscellaneous Diagnostic and Therapeutic Procedures

Note: Adapted from International Classification of Diseases 9th Revision, p. vi. Copyright 2014 by Practice Management Information Corporation.

Table 4

ICD-10 PCS Procedure Code Groups

Codes	Descriptions
0016070-0YWBXYZ	Section 0 - Medical and Surgical
102073Z-10Y07ZY	Section 1 - Obstetrics
2W00X0Z-2Y55X5Z	Section 2 - Placement
30230AZ-3E1Y38Z	Section 3 - Administration
4A0002Z-4B0FXVZ	Section 4 - Measurement and Monitoring
5A02110-5A2204Z	Section 5 - Extracorporeal or Systemic Assistance and Performance
6A0Z0ZZ-6ABT0BZ	Section 6 - Extracorporeal or Systemic Therapies
7W00X0Z-7W09X9Z	Section 7 - Osteopathic
8C01X6J-8E0ZXY6	Section 8 - Other Procedures
9WB0XBZ-9WB9XLZ	Section 9 - Chiropractic
B00B0ZZ-BY4GZZZ	Section B - Imaging
C0101ZZ-CW7YYZZ	Section C - Nuclear Medicine
D0000ZZ-DWY6FZZ	Section D - Radiation Therapy
F003GKZ-F15Z7ZZ	Section F - Physical Rehabilitation and Diagnostic Audiology
GZ10ZZZ-GZJZZZZ	Section G - Mental Health
HZ2ZZZZ-HZ99ZZZ	Section H - Substance Abuse Treatment
X2A5312-XY0VX83	Section X - New Technology
02VW0DJ-XNS4432	-/+ Deleted, Replaced, Expanded Codes

Note: Information obtained at https://www.findacode.com/code-set.php?set=ICD10PCS

4.2.3 HCPCS Procedure codes. CMS, in coordination with the American Medical Association, publishes the Healthcare Common Procedure Coding System (HCPCS). “HCPCS is a collection of standardized codes that represent medical procedures, supplies, products, and services. The codes are used to facilitate the processing of health insurance claims by Medicare and other insurers… HCPCS is divided into two subsystems, Level I and Level II. Level I comprise Current Procedural Terminology® codes (CPT), each consisting of five numeric digits, some containing an additional two-digit modifier that helps to describe additional or unusual services or circumstances. Level II HCPCS codes identify products, supplies, and services not included in CPT. Level II codes consist of a letter followed by four numeric digits" (National Institute of Health, 2020).

Additionally, CMS organizes the HCPCS codes into medical service groups (see Table 5). Our research utilizes these groups to organize and simplify the data used in our study. For reference only, we also include a detailed listing of the HCPCS Level II codes (see Table 6).

Table 5

HCPCS Level I Code Groupings

Codes	Description
99201-99499	Evaluation and Management
00100-01999	Anesthesia
10021-69990	Surgery
76496-79999	Radiology
80047-89398	Pathology and Lab
90281-99199	Medicine
A0001-Z9999	Level II (transportation, materials, supplies)
All other	Other or not-defined

Note: Adapted from two sources. CPT Standard Edition 2015, p. xii. Copyright 2014 by American Medical Association. HCPCS National Level II Medicare Codes 2014. Copyright 2013 by Practice Management Information Corporation.

Table 6

HCPCS Level II Code Sections

Codes	Description
A0000-A0999	Transportation
A4000-A7509	Medical and Surgical Supplies
A9000-A9999	Miscellaneous and Experimental
B0000-B9999	Enteral and Parenteral Therapy
C0000-C9999	Temporary Hospital Outpatient Prospective Payment System
D0000-D9999	Dental Codes
E0000-E9999	Durable Medical Equipment
G0000-G9999	Temporary Procedures and Professional Services
H0000-H9999	Rehabilitative Services
J0000-J8999	Drugs Administered Other Than Oral Method
J9000-J9999	Chemotherapy Drugs
K0000-K9999	Temporary Codes for Durable Medical Equipment Regional Carriers
L0000-L4999	Orthotic Services
L5000-L9999	Prosthetic Procedures
M0000-M9999	Medical Services
P0000-P9999	Pathology and Laboratory
Q0000-Q9999	Temporary Codes
R0000-R9999	Diagnostic Radiology Services
S0000-S9999	Private Payer Codes
T0000-T9999	State Medicaid Agency Codes
V0000-V2999	Vision Services
V5000-5999	Hearing Services

Note: Adapted from HCPCS National Level II Medicare Codes 2014, pp. 2-3. Copyright 2013 by Practice Management Information Corporation.

4.2.4 Diagnostic related groups. Hospitalized patients are classified into clinically comparable groups using categorizations called Diagnostic Related Groups (DRGs) that acknowledge each patient's illness severity, prognosis, treatment difficulty, need for intervention, and resource intensity. These categories collectively represent degrees of clinical care complexity. According to CMS: "The DRGs are a patient classification scheme which provides a means of relating the type of patients a hospital treats (i.e., its case mix) to the costs incurred by the hospital" (CMS, 2019). Table 7 displays the categorization of DRG code groupings.

Table 7

Diagnostic Related Group Codes

Codes Range	Description
001-017	Pre-MDC
020-103	Diseases & Disorders of the Nervous System
113-125	Diseases & Disorders of the Eye
129-159	Diseases & Disorders of the Ear, Nose, Mouth & Throat
163-208	Diseases & Disorders of the Respiratory System
215-320	Diseases & Disorders of the Circulatory System
326-395	Diseases & Disorders of the Digestive System
405-446	Diseases & Disorders of the Hepatobiliary System & Pancreas
453-566	Diseases & Disorders of the Musculoskeletal System & Connective Tissue
570-607	Diseases & Disorders of the Skin, Subcutaneous Tissue & Breast
614-645	Endocrine, Nutritional & Metabolic Diseases & Disorders
652-700	Diseases & Disorders of the Kidney & Urinary Tract
707-730	Diseases & Disorders of the Male Reproductive System
734-761	Diseases & Disorders of the Female Reproductive System
768-833	Pregnancy, Childbirth & the Puerperium
790-795	Newborns & Other Neonates with Conditions Originating in the Perinatal Period
799-816	Diseases & Disorders of Blood, Blood Forming Organs, Immunologic Disorders

820-849	Myeloproliferative Diseases & Disorders, Poorly Differentiated Neoplasms
853-872	Infectious & Parasitic Diseases, Systemic or Unspecified Sites
880-887	Mental Diseases & Disorders
895-897	Alcohol/Drug Use & Alcohol/Drug-Induced Organic Mental Disorders
901-923	Injuries, Poisonings & Toxic Effects of Drugs
927-935	Burns
939-951	Factors Influencing Health Status & Other Contacts with Health Services
955-965	Multiple Significant Trauma
969-977	Human Immunodeficiency Virus Infections
981-989	O.R. Procedure Unrelated To Principal Diagnosis With or Without CC / MCC
998-998	Principal Diagnosis Invalid As Discharge Diagnosis
999-999	Ungroupable

Note: Adapted from information obtained at https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareFeeforSvcPartsAB/downloads/DRGdesc08.pdf

Another means of organizing DRGs is to assign each code to either of two categories: surgical and medical. These categorizations enable researchers to differentiate between these two basic types of hospital admissions based on the DRG code assigned for each admission (see Table 8).

Table 8

DRGs Sorted by Admission Type

DRG Code Range	Admission Type
001-042	Surgical
052-103	Medical
113-117	Surgical
121-125	Medical
129-139	Surgical
146-159	Medical
163-168	Surgical
175-208	Medical
215-265	Surgical
280-316	Medical

326-358	Surgical
368-395	Medical
405-425	Surgical
432-446	Medical
453-517	Surgical
533-566	Medical
573-585	Surgical
592-607	Medical
614-630	Surgical
637-645	Medical
652-675	Surgical
682-700	Medical
707-718	Surgical
722-730	Medical
734-750	Surgical
754-761	Medical
765-770	Surgical
774-795	Medical
799-804	Surgical
808-816	Medical
820-830	Surgical
834-849	Medical
853-858	Surgical
862-872	Medical
876-876	Surgical
880-897	Medical
901-909	Surgical
913-923	Medical
927-929	Surgical
933-935	Medical
939-941	Surgical
945-951	Medical
955-959	Surgical
963-965	Medical
969-970	Surgical
974-977	Medical
981-989	Surgical
Other	Other

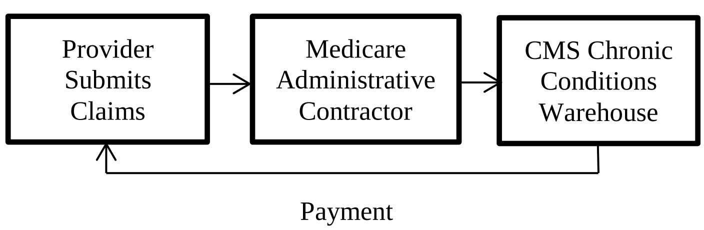
Note: Adapted from information obtained at https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareFeeforSvcPartsAB/downloads/DRGdesc08.pdf

4.3 Medicare Data Sources

Our study uses restricted, highly protected data available from CMS. These restricted datasets, called Research Identifiable Files (RIF), contain actual data from all Medicare beneficiaries' reportable healthcare service activities. These are the most comprehensive datasets available for our study. CMS maintains these files in its Chronic Conditions Warehouse, a virtual data repository for researchers. Access to RIFs requires a formal, multi-month application process that includes research justification and data management and security plans that must receive approval by representatives from CMS and its designated contractors.

Traditional Medical data come from the providers' (e.g., hospitals, doctors, home health agencies) claims submitted to CMS and its contractors and contain demographical, clinical coding, and financial data. The claims submittal and payment processes, also called "adjudication," are complex, comprehensive, and differing among the provider types. A detailed examination of the process is available at https://www.cms.gov/Regulations-and-Guidance/Guidance/Manuals/downloads/clm104c01.pdf. Exhibit 10 offers a simplified portrayal of the claims submission and payment process.

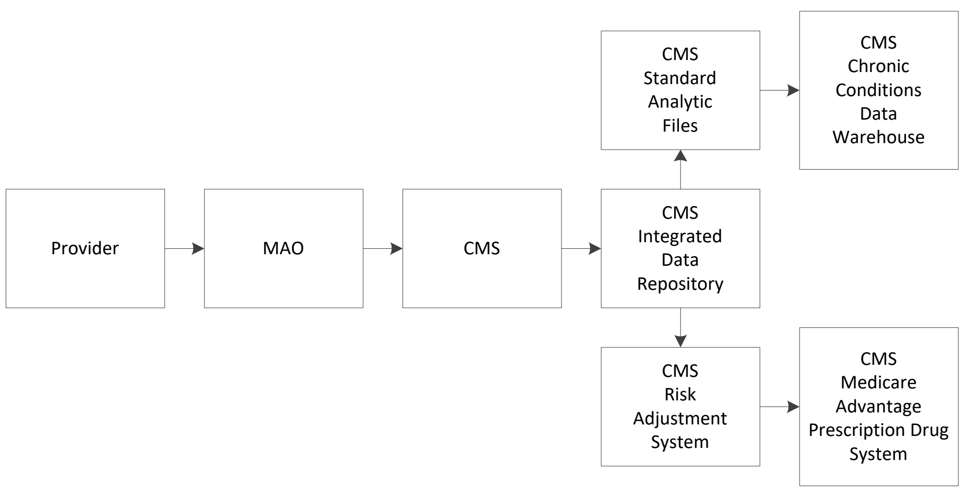
Exhibit 10. Claims Adjudication and Payment



Traditional Medicare adjudicated claims data include several financial variables such as the providers' submitted charges, the allowed payments from Medicare, the amounts paid to providers, and the patients' amounts due. Service start dates and stop dates enable researchers to count and determine the length of each episode of care.

Medicare Advantage information, called encounter data, is received from the MAOs (i.e., the private insurers). As a condition of participation in the MA program, the MAOs must report to CMS specific patient-provider encounters and related information during the contract period. In turn, the MAOs require each contracted provider to submit to them their patient encounter data. A detailed description of the process is available in the Medicare Managed Care Manual (www.cms.gov, 2020). Exhibit 11 is a simplified portrayal of CMS' encounter data collection and storage process.

Exhibit 11. Encounter Data Processing and Storage



One of the Medicare Advantage data limitations is that provider payments and cost information are not included. Instead, the files include the dates, counts, and descriptions of service types received by the beneficiaries and plan and demographical information.

Our conversations with MAOs inform us that Medicare Advantage fee payments to their networks' non-RB providers are approximately comparable to Traditional

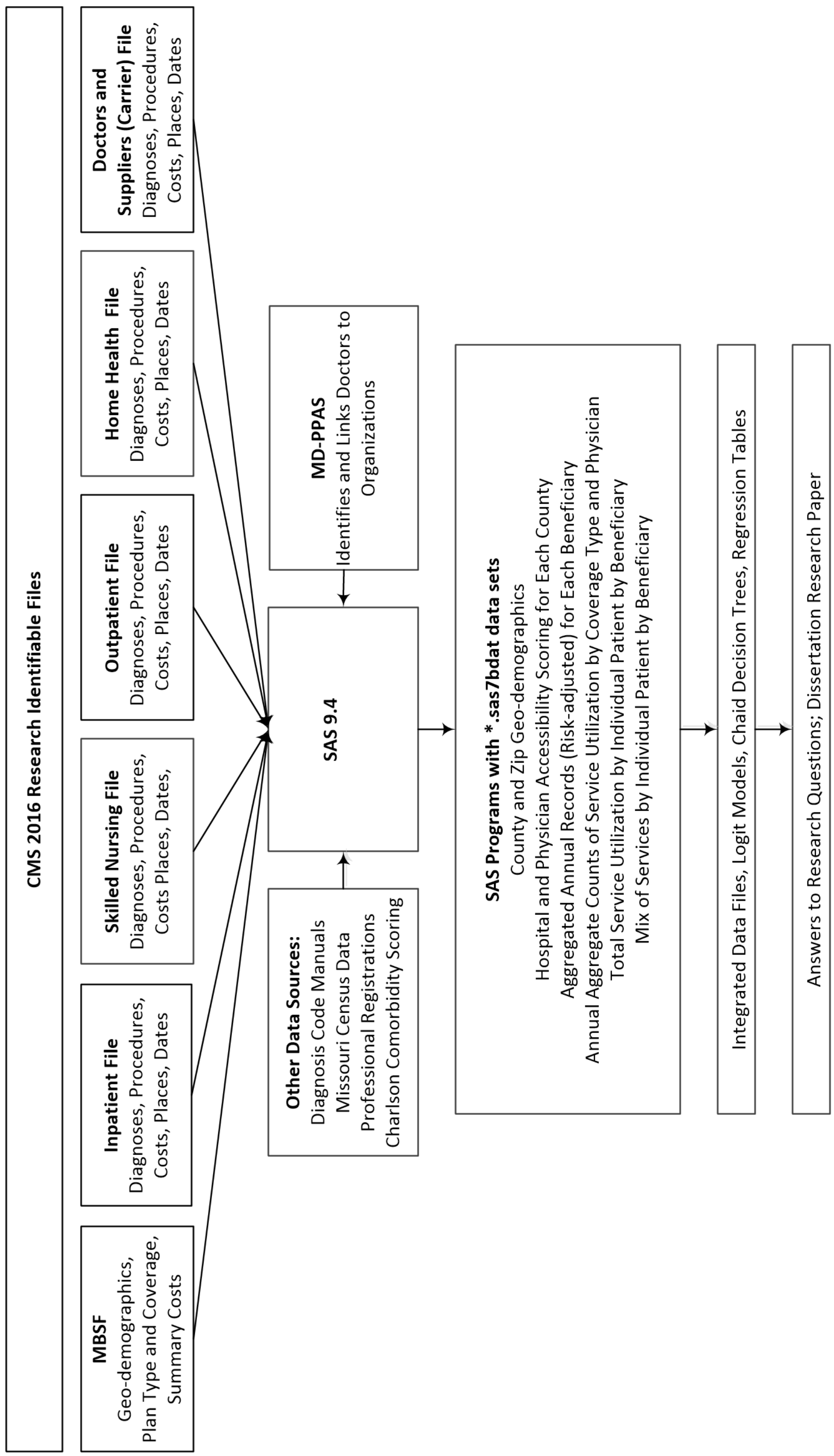
Medicare fee payments to providers. A recent study by a prominent research group reported a similar finding (Curto, Einav, Finkelstein, Levin, and Bhattacharya, 2017). Therefore, one may choose to use Traditional Medicare fees as proxies for the cost of Medicare Advantage services to estimate some of the economic effects of the various plan choices.

4.3.1 Medicare Data Sample. Data for this dissertation were acquired to support a four-year program of research under strict protocols approved by the Center for Medicare and Medicaid Services. Following a six-month process for approval of the research plan and data protection practices, we received our data in the form of 396 encrypted, compressed RIFs, equating to approximately 55 gigabytes and representing the healthcare records for 999,999 of Missouri's 1,160,093 Medicare beneficiaries. They were installed on the dedicated HIPAA-compliant server for this research program at the University of Missouri-St. Louis,

The CMS provides an encrypted beneficiary ID, a pseudo-identifier to enable researchers to link records in various files to individual beneficiaries while protecting their privacy. An annual "master beneficiary summary file" contains high-level summaries of patients' demographics, residential status, types of Medicare coverage over the year, service utilization, and costs of service delivered under FFS reimbursement. In separate files, encounter and diagnostic data are provided under five service categories: a) inpatient, b) hospital-based outpatient, c) carrier (doctors and other non-hospital suppliers), d) home-health assistance, and e) skilled nursing facility.

Several records in the encounter files often apply to the same service encounter. For each type of service, we generally considered all records ascribed to a particular date as representing a single incident of related service activity in a particular category. We constructed summaries of procedures and diagnoses ascribed to each day of the year for each of the five services and merged them with the Master Beneficiary summaries and complementary information from other sources to build a consolidated record for each Medicare beneficiary. The consolidated record thus indicates medical services received, diagnostic information, access to medical services, and demographic data tied to individuals' place of residence. We used SAS 9.4 for data consolidation and transformation and for most of the statistical analysis. Exhibit 12 displays a schematic that depicts the sources and uses of data for this research.

Exhibit 12. Sources and Uses of Data



4.3.2 Beneficiary record development. Our research requires a complete, annual healthcare record for each beneficiary that reflects services covered under the insurance plan while the person is resident in the same location over the entire year. Mid-year changes to coverage and plan types could introduce bias into the study. From the plan identification numbers, along with the beneficiary's months of coverage under each plan, we could determine if a beneficiary was in the same plan for the entire year. For our study population, we, therefore, excluded the records of beneficiaries not having a consistent 12-month coverage in the same plan. We also excluded beneficiaries under age 65, those with address changes, and those in hospice or experiencing an end-stage renal disease. The reasons for exclusions are described in Table 9.

Table 9

Beneficiary Records Excluded from the Study

Excluded Group	Reason for Exclusion
Beneficiaries under age 65	To focus the study on the elderly population by omitting younger beneficiaries who receive Medicare coverage due to their physical disabilities
Beneficiaries with either non-Missouri residences or non-Missouri mailing addresses	To eliminate the effects of healthcare utilization that may occur outside of the state
Beneficiaries with mid-year zip code changes	To eliminate the effects of possible changes in provider access
Beneficiaries with mid-year plan changes	To eliminate the effects of possible changes in provider access and benefits coverage
Beneficiaries receiving hospice care	Medicare Advantage plans generally do not pay for hospice care benefits
Beneficiaries experiencing end-stage renal disease	Beneficiaries in this category may receive care through a special needs program (SNP), and access to SNP plans varies throughout the state

In Table 10, we display the counts and percentages of total Missouri Traditional Medicare (FFS) and Medicare Advantage (HMO) enrollees, the counts and percentages for the random sample records, and the counts and percentages for the normalized records used in our study. We note that the FFS program provides insurance coverage and benefits for special classes of patients (e.g., hospice, end-stage renal disease) that may be different from those generally available in the HMO plans. Consequently, compared to the HMO population, a higher proportion of FFS beneficiaries are excluded from the study. This adjustment helps to assure that the FFS and HMO study populations have comparable, basic schedules of benefits. Our study population includes 55.7% of all Missouri Medicare beneficiaries, thus enabling a robust study with a very high confidence level.

Table 10

Beneficiary Counts (2016)

Measure	FFS	HMO/Other	Total
Total Number of Missouri Medicare Beneficiaries	812,974	347,119	1,160,093
% of Total Missouri Medicare Beneficiaries	70.1%	29.9%	100.0%
Total Number of Random Sample Beneficiaries	708,665	291,334	999,999
% of Total Random Sample Beneficiaries	87.2%	83.9%	100.0%
Total Number of Included Beneficiaries	432,765	213,435	646,200
% of Missouri Beneficiaries Represented by Study Sample	53.2%	61.5%	55.7%

We created summaries of annual service tallies that show mean usage by both the included and excluded populations for FFS and HMO beneficiaries (see Tables 11 and 12). The tables reveal material differences in the means for several service categories (also see SAS output in Appendices J and K). Reasons for the differences vary. Among those excluded are individuals who died during the year, those who had partial coverage for some other reason, and individuals who moved to another geographic area.

Table 11

Difference in Means for FFS Study Populations

Service Type	Included Sample	Excluded Sample	% Difference
Inpatient Discharges	1.576	1.953	24%
Outpatient Services	9.807	17.301	76%
Carrier Services	46.978	41.329	-12%
Home Health Service	18.102	17.696	-2%
SNF Discharges	3.320	3.060	-8%

Table 12

Difference in Means for HMO Study Populations

Service Type	Included Sample	Excluded Sample	% Difference
Inpatient Discharges	1.521	1.790	15%
Outpatient Services	5.830	8.804	34%
Carrier Services	42.938	48.376	11%
Home Health Service	11.786	10.736	-10%
SNF Discharges	1.940	2.024	4%

Plan type and demographical information. Using the pseudo-identifier, we extract from the Master Beneficiary Summary File (MBSF) the desired variables to construct a relevant portion of each Traditional Medicare and Medicare Advantage beneficiary's demographical record. The complete listing of MBSF variable names and descriptors are in Appendix B.

Table 13 displays the names and descriptions of the variables used to develop each beneficiary's demographical and plan type profiles. The demographics include each beneficiary's unique identifying number, year of coverage (2016), gender, race, and place of residence as defined by county, state, and zip code. The insurance plan variables are used to describe the type of insurance coverage(s), as defined by an insurance plan contract number, maintained by each beneficiary, and the length of time, in months, that the coverage(s) was(were) in force.

Table 13

Demographical and Insurance Plan Variables

Group	SAS Variable Long Name	Description
Demographics	BENE_ID	Beneficiary identification number (encrypted)
	RFRNC_YR	Reference year (2016) to confirm that beneficiary's data is for the study period
	AGE_AT_END_REF_YR	Beneficiary age at year-end
	SEX_IDENT_CD	Beneficiary sex (unknown, male, female)
	BENE_RACE_CD	Beneficiary race (seven categories)
	COUNTY_CD	Beneficiary county code base on mailing address
	STATE_CD	Beneficiary state code based on mailing address
	ZIP_CD	Beneficiary zip code based on mailing address
Insurance plan	BENE_HMO_CVRAGE_TOT_MONS	Number of months beneficiary received their benefits through an MA plan
	PTC_CNTRCT_ID_01	Beneficiary's MA plan identification number in January
	PTC_CNTRCT_ID_12	Beneficiary's MA plan identification number in December

Summary file. Among the data received for our study is a file named "Master Beneficiary Summary File Cost & Use Segment" (MBSF). For each Traditional Medicare beneficiary, this dataset contains annual summaries of patient care activity and associated costs for each of several care categories. These data summarize many of the provider payment elements of the study and are useful for validating the summation of specific line item values contained within other data sets. The variables examined from this file appear in Table 14. The MBSF Cost &Use segment contains very limited and incomplete cost-of-service information for Medicare Advantage beneficiaries, and that data is not useful for this study.

Table 14

Cost and Use Segment File: Variables for Traditional Medicare Beneficiaries

Group	SAS Variable Long Name	Description
Acute Inpatient	ACUTE_STAYS	Number of acute inpatient stays
	ACUTE_COV_DAYS	Number of acute inpatient days
	ACUTE_MDCR_PMT	Acute inpatient payments from Medicare
	ACUTE_PERDIEM_PMT	Acute inpatient per diem payments from Medicare
	ACUTE_PRMRY_PMT	Acute inpatient payments from non-Medicare sources
	READMISSIONS	Number of readmissions to Missouri hospitals within 30 days of a previous stay
Other Inpatient	OIP_STAYS	Other (non-acute) inpatient stays
	OIP_COV_DAYS	Number of other (non-acute) inpatient days
	OIP_MDCR_PMT	Other (non-acute) inpatient payments from Medicare
	OPI_PERDIEM_PMT	Other (non-acute) inpatient per diem payments from Medicare
	OIP_PRMRY_PMT	Other (non-acute) inpatient payments from non-Medicare sources
Skilled Nursing	SNF_STAYS	Number of skilled nursing stays
	SNF_COV_DAYS	Number of skilled nursing days
	SNF_MDCR_PMT	Skilled nursing payments from Medicare
	SNF_PRMRY_PMT	Skilled nursing payment from non-Medicare sources
	SNF_BENE_PMT	Skilled nursing payment co-insurance and deductible payment amounts
Hospital Outpatient	HOP_VISITS	Hospital outpatient visits
	HOP_MDCR_PMT	Hospital outpatient payments from Medicare
	HOP_PRMRY_PMT	Hospital outpatient payments from non-Medicare sources
	HOP_BENE_PMT	Hospital outpatient co-insurance and deductible payment amounts
Home Health	HH_VISITS	Home health visits
	HH_MDCR_PMT	Home health payments from Medicare
	HH_PRMRY_PMT	Home health payment from non-Medicare sources

Inpatient file. Inpatient care occurs in a Medicare-certified facility where a patient incurs an overnight stay that generally includes two or more midnights. (Some single night stays are classified as observation-only stays and do not meet the inpatient admission criteria.) Using each beneficiary's unique identifier, we extract from the merged inpatient file the specific variables to construct each beneficiary's inpatient facilities record. The complete listing of inpatient variable names and descriptors appear in Appendix B, but generally are described as

- pseudo-identifier;
- discharge dates;
- facility identifiers;
- ICD diagnosis codes.

Also, the diagnosis codes (ICD-9/10) recorded in any inpatient admission are placed into their appropriate group as defined previously.

Skilled Nursing Facility (SNF) file. A beneficiary may receive skilled nursing care provided for a limited time (on a short-term basis) if all of these conditions are met:

- the beneficiary has Medicare Part A (hospital coverage) and a balance of days left in their benefit period;
- the beneficiary is discharged from a qualifying hospital stay;
- the beneficiary's doctor has decided that daily skilled care is required and that care must be given by, or under the supervision of, a skilled nursing or therapy staff;
- the skilled services occur in a Medicare-certified SNF; and the skilled services are required for a medical condition that's either (a) a hospital-related medical condition treated during a qualifying 3-day inpatient hospital stay, even if it was not the reason for the hospital admission, or (b) a condition that started while receiving care in the SNF for a hospital-related medical condition (for example, an infection that requires IV antibiotics while receiving SNF care).

Using each beneficiary's unique identifier, we extract from the merged SNF file the specific variables to construct each beneficiary’s skilled nursing activity record. Appendix C displays the names and descriptors, but they generally can be described as follows:

- pseudo-identifier;
- facility identifiers;
- discharge dates;
- ICD codes.

Also, the ICD codes recorded in any SNF admission are assigned to their appropriate group.

Hospital-based outpatient services file. Outpatient services are generally received in places other than an inpatient hospital or medical practice setting. They can be located on a hospital campus or off a hospital campus. The hospital’s organizational structure, including its arrangements for reimbursement from CMS, determines if an off-campus service is a hospital-based service. Examples of hospital outpatient services include but are not limited to, imaging, laboratory, therapies, endoscopic procedures, emergency department visits, urgent care, and ambulatory surgeries. Using each beneficiary's unique identifier, we extract from the merged outpatient file the specific variables to construct each beneficiary’s outpatient services record. The variable names and descriptors appear in Appendix D but generally are described as follows:

- pseudo-identifier;
- facility identifiers;
- encounter dates;

- HCPCS codes;
- ICD codes.

Also, the HCPCS and ICD codes recorded from any outpatient event are assigned to their appropriate groups.

Home health care. Traditional Medicare beneficiaries with either or both Medicare Part A and Part B coverage and who meet all of these conditions are eligible to receive home health care services (Health Services Coverage, https://www.medicare.gov/coverage/home-health-services):

- the beneficiary is under the care of a doctor and is receiving services under a plan of care created and reviewed regularly by a doctor;
- a doctor has certified that one or more of the following is needed:
  - intermittent skilled nursing care (other than drawing blood);
  - physical therapy, speech-language pathology, or continued occupational therapy services (note: these services are covered only when the services are a specific, safe and effective treatment for the condition being treated);
  - the amount, frequency, and time period of the services needs to be reasonable, and they need to be complex or such that only qualified therapists can do them safely and effectively;
  - either (1) beneficiary's condition must be expected to improve in a reasonable and generally predictable period of time, or (2) a skilled therapist is needed to safely and effectively create a maintenance program for the condition being treated, or (3) a skilled therapist is

needed to safely and effectively do maintenance therapy for a condition.

- the home health agency is certified by Medicare;
- the beneficiary is homebound, as certified by a doctor; and
- the beneficiary does not need more than part-time or "intermittent" skilled nursing care.

MAOs generally impose similar requirements on their members, but the MAOs are allowed to expand these benefits as long as the Traditional Medicare benefits are included in their plans.

Using each beneficiary's unique identifier, we extract from the merged home health files the specific variables to construct each beneficiary’s home health care record. The variable names and descriptors appear in Appendix E, but generally can be described as follows:

- pseudo-identifier;
- provider identifiers;
- encounter dates;
- HCPCS codes;
- ICD codes

Also, the HCPCS and ICD codes recorded with any outpatient event are placed into their appropriate groups.

Carrier file. This care category includes services performed by physicians, nurse practitioners, therapists, and other licensed practitioners. It also may include certain institutional providers such as clinical laboratories, urgent care centers, free-standing/walk-in clinics, ambulance services, suppliers, and stand-alone ambulatory surgical centers. Using each beneficiary's unique identifier, we extract from the merged carrier file the specific variables to construct each beneficiary's carrier records. The variable names and descriptors for this file appear in Appendix F, but generally can be described as follows:

- pseudo-identifier;
- encounter dates;
- provider identifiers (NPI) codes;
- provider taxonomy (specialty) codes;
- HCPCS codes;
- ICD codes.

Also, the HCPCS and ICD codes recorded from any carrier event are placed into their appropriate groups.

4.4 CCMI score

The CCMI score is a predictor of a beneficiary's survival rate during the next year. A CCMI score is calculated for each service category for each beneficiary using weighted values applied to specific ICD-10 codes reported by their providers. The ICD-10 coding algorithm (see Exhibit 13) used in our study was proposed by Quan et al. (2005). If any of the eligible ICD-10 codes appear one or more times in a beneficiary's aggregated record, the score for that code enters the CCMI calculation. The sum of the values represents the CCMI score placed into each beneficiary's aggregated record. The score can range from 0 (no serious diseases) to 32 (multiple co-morbidities). Lower CCMI scores predict higher survival rates, and higher scores predict lower survival rates.

In this study, our application of a CCMI score is its use as an explanatory variable relating to a beneficiary's plan choice and service utilization in each care setting.

Exhibit 13. Charlson Comorbidity Algorithm

Comorbidities	Score	Deyo's ICD-9-CM +	ICD-10 *	Enhanced ICD-9-CM *
Myocardial infarction	1	410.x, 412.x	I21.x, I22.x, I25.2	410.x, 412.x
Congestive heart failure	1	428.x	I09.9,I11.0, I13.0, I13.2, I25.5, I42.0, I42.5-I42.9, I43.x, I50.x, P29.0	398.91, 402.01, 402.11, 402.91, 404.01, 404.03, 404.11, 404.13, 404.91, 404.93, 425.4-425.9, 428.x
Peripheral vascular disease	1	443.9, 441.x, 785.4, V43.4 Procedure 38.48	I70.x, I71.x, I73.1, I73.8, I73.9, I77.1, I79.0, I79.2, K55.1, K55.8, K55.9, Z95.8, Z95.9	093.0, 437.3, 440.x, 441.x, 443.1-443.9, 447.1, 557.1, 557.9, V43.4
Cerebrovascular disease	1	430.x-438.x	G45.x, G46.x, H34.0, I60.x-I69.x	362.34, 430.x-438.x
Dementia	1	290.x	F00.x-F03.x, F05.1, G30.x, G31.1	290.x, 294.1, 331.2
Chronic pulmonary disease	1	490.x-505.x, 506.4	I27.8, I27.9, J40.x-J47.x, J60.x-J67.x, J68.4, J70.1, J70.3	416.8, 416.9, 490.x-505.x, 506.4, 508.1, 508.8
Rheumatic disease	1	710.0, 710.1, 710.4, 714.0-714.2, 714.81, 725.x	M05.x, M06.x, M31.5, M32.x-M34.x, M35.1, M35.3, M36.0	446.5, 710.0-710.4, 714.0-714.2, 714.8, 725.x
Peptic ulcer disease	1	531.x-534.x	K25.x-K28.x	531.x-534.x
Mild liver disease	1	571.2, 571.4-571.6	B18.x, K70.0-K70.3, K70.9, K71.3-K71.5, K71.7, K73.x, K74.x, K76.0, K76.2-K76.4, K76.8, K76.9, Z94.4	070.22, 070.23, 070.32, 070.33, 070.44, 070.54, 070.6, 070.9, 570.x, 571.x, 573.3, 573.4, 573.8, 573.9, V42.7
Diabetes without chronic complication	1	250.0-250.3, 250.7	E10.0, E10.l, E10.6, E10.8, E10.9, E11.0, E11.1, E11.6, E11.8, E11.9, E12.0, E12.1, E12.6, E12.8, E12.9, E13.0, E13.1, E13.6, E13.8, E13.9, E14.0, E14.1, E14.6, E14.8, E14.9	250.0-250.3, 250.8, 250.9
Diabetes with chronic complication	2	250.4-250.6	E10.2-E10.5, E10.7, E11.2-E11.5, E11.7, E12.2-E12.5, E12.7, E13.2-E13.5, E13.7, E14.2-E14.5,	250.4-250.7
Hemiplegia or paraplegia	2	344.1, 342.x	G04.1, G11.4, G80.1, G80.2, G81.x, G82.x, G83.0-G83.4, G83.9	334.1, 342.x, 343.x, 344.0-344.6, 344.9
Renal disease	2	582.x, 583-583.7, 585.x, 586.x, 588.x	I12.0, I13.1, N03.2-N03.7, N05.2-N05.7, N18.x, N19.x, N25.0, Z49.0-Z49.2, Z94.0, Z99.2	403.01, 403.11, 403.91, 404.02, 404.03, 404.12, 404.13, 404.92, 404.93, 582.x, 583.0-583.7, 585.x, 586.x, 588.0, V42.0, V45.1, V56.x
Any malignancy, including lymphoma and leukemia, except malignant neoplasm of skin	2	140.x-172.x, 174.x-195.8, 200.x-208.x	C00.x-C26.x, C30.x-C34.x, C37.x-C41.x, C43.x, C45.x-C58.x, C60.x-C76.x, C81.x-C85.x, C88.x, C90.x-C97.x	140.x-172.x, 174.x-195.8, 200.x-208.x, 238.6
Moderate or severe liver disease	3	456.0-456.21, 572.2-572.8	I85.0, I85.9, I86.4, I98.2, K70.4, K71.1, K72.1, K72.9, K76.5, K76.6, K76.7	456.0-456.2, 572.2-572.8
Metastatic solid tumor	6	196.x-199.1	C77.x-C80.x	196.x-199.x
AIDS/HIV	6	042.x-044.x	B20.x-B22.x, B24.x	042.x-044.x

Source:

+ Deyo RA, Cherkin DC, Ciol MA. Adapting a clinical comorbidity index for use with ICD-9-CM administrative databases. *J Clin Epidemiol.* 1992; 45: 613-9.

* Quan H, Sundararajan V, Halfon P, et al. Coding algorithms for defining Comorbidities in ICD-9-CM and ICD-10 administrative data. *Med Care.* 2005 Nov; 43(11): 1130-9.

4.5 Access

We also investigate if a beneficiary's access to medical care affects service utilization. We define "access" four ways: physician access, hospital access, financial resources, and level of education. We developed these access scores using the CMS files and third-party sources, including the Missouri Division of Professional Registration, the Essence 2016 Provider Directory, the Missouri Office of Primary Care Health and Rural Health, the Missouri Department of Health and Senior Services, and the U.S. Census Bureau.

4.5.1 Physician access score. Using data from the Missouri Division of Professional Registration, we identified all physicians, both allopathic and osteopathic, having a primary business address in a Missouri county. We totaled the number of physicians in each county who were not under disciplinary action and had an active license since 2015. Physician count by county is an explanatory variable. The resulting directory is displayed in Appendix H.

4.5.2 RB PCP roster. We wish to note that we have been unable to locate a data set that identifies the individual PCPs who participate in Medicare Advantage RB arrangements. Consequently, we do not know how many PCPs have experience with these types of agreements, and it is likely we could find them only with an extensive and expensive search. Moreover, if such a search and identification process were feasible, it presumes that PCPs are willing to cooperate and reveal the contract terms and other arrangements with their MAOs. Furthermore, our conversations with PCPs and MAOs, as well as a review of their contracts, indicate the contract information may be limited or unavailable. There are at least three reasons: (a) various confidentiality provisions exist in the MAO/PCPs contracts, (b) various disclosure prohibitions exist in the provider group/provider contracts (e.g., Harmony IPA and its participating providers), and (c) proprietary, closely guarded information is held by the MAOs. Collectively, these constraints significantly hinder one’s ability to create an extensive directory of RB PCPs, including descriptions of critical financial elements contained in their contracts with MAOs.

Fortunately, our familiarity with Harmony and two of its MAO presented the opportunity to understand the RB arrangements with this group of PCPs. We learned from our conversations with the MAOs that there are similarly structured contracts with many PCPs in their plan networks. For example, we learned that Harmony is engaged in an RB arrangement with an MAO called “Essence.” Three sources within Essence confirmed that Harmony’s RB contract is structured similarly to those involving 200 PCPs in Essence’s St. Louis-area network. Accordingly, when examining characteristics of the plans in which Harmony participates, we also can assess the presence of RB PCPs (including Harmony PCPs) and evaluate whether their collective presence affects healthcare service utilization.

4.5.3 Gatekeeping. The RB PCP typically is a medical “gatekeeper” who determines how, when, and where a patient will receive services. The RB PCP may choose to refer a patient for a service rendered at a hospital-based clinic, a specialty medical practice, or other clinics (any of which likely requires an external referral for an appointment on a future date). Alternatively, the RB PCP may render that same service on the same day the patient visits the PCP’s medical practice. By rendering same day service in the PCP’s office, the patient experiences greater convenience and possibly avoids a co-pay or other costs associated with a visit to the external provider. If a referral is warranted, then the PCP may choose to direct or refer patients to facilities, providers, and services having competitive prices. These gatekeeping functions enable the PCP to engage in medical care and cost management oversight that may not be done by nongatekeepers. Accordingly, our study examines if the Essence beneficiaries use services differently than beneficiaries in the other Traditional Medicare and Medicare Advantage plans.

4.5.4 Hospital proximity. We use the Missouri Office of Primary Care and Rural Health's (MOPCRH) bi-annual 2018 report to quantify hospital access for each Missouri county. We verified that the hospitals listed in the report were operational in 2016. We also asked a MOPCRH representative to describe the method by which hospital distances from each non-hospital county were determined, as stated in the report. The representative indicated that the hospital distances were calculated by traveling the most direct, primary roadways from the county seat to the nearest hospital. When we asked for the definition of a county seat, the representative told us that information was not available because the staff and consultants engaged in the study were no longer with the office. Using Google maps, we tested the distances by conducting a visual inspection of the roadways nearest the approximate geographical center of each of five no-hospital counties (from differing areas of the state) to the nearest hospitals in their regions. Using the Google maps driving distance results, we found that the tested distances were within the parameters defined in the report. Therefore, we accepted the report's travel distance assumptions. We then assigned three groupings: (a) counties containing at least one general access hospital, (b) counties without a hospital but having one within a distance of 27 miles or less, and (c) counties with no general access hospitals within 28 miles of the county seat. Each group was assigned a code of 1, 2, or 3. The hospital access results are displayed in Appendix I.

4.5.5 Missouri census data. One objective of our study is to consider explanatory variables that are not contained within the CMS datasets. We specifically include surrogate variables that predict each beneficiary's financial resource and level of education based on individuals who live in the beneficiary's residential neighborhood. To create these variables, we obtained data for geographic regions from the Missouri Census Data Center (MCDC). The MCDC participates in a cooperative program with the U.S. Bureau of the Census (Bureau). An innovation introduced by the Bureau as part of the 2000 U.S. census effort was creating Zip Code Tabulations Areas (ZCTAs) as an alternative to using zip codes for constructing data analyses. From the Bureau's perspective, zip codes represent mail delivery locations that may not always represent logical, spatial areas defined by geographical boundaries. Also, there are some zip codes with little to no residential populations, such as those representing a specific location for a group of post office boxes or a very sparsely populated rural area. To overcome these deficiencies, the Bureau invoked the ZCTA methodology, based on census blocks (which include the residence zip codes) rather than the zip codes themselves, to represent geographically definable areas meeting minimum population thresholds (census.gov, n.d.).

Also under the purview of the Bureau is the American Community Survey (ACS). The ACS is an ongoing, long-form survey taken both during the decennial censuses and in each interim year. The ACS seeks to capture various characteristics of the U.S. population-based on survey answers supplied from approximately 3.5 million households (census.gov, n.d.). The survey tabulations generate statistically relevant summaries of demographical data applied to a geographic region such as a nation, state, county, or

ZCTA. With the annual updates, longitudinal data can be structured to create more accurate estimates, thereby improving the accuracy of estimates drawn from a single point in time (such as the decennial census year). For our study, we access the MCDC-supplied dataset containing demographical estimates for financial resources and levels of education assigned to the Missouri ZCTAs based on a five-year average (2014-2018) of ASC survey responses. We incorporate the census data by matching our beneficiaries' residence zip codes to their respective ZCTAs.

Financial resource. Whether in Traditional Medicare or Medicare Advantage plans, beneficiaries may incur a personal cost for access to and use of medical services. The amount of personal cost is, in part, determined by plan selection and the associated schedule of benefits. Personal costs can include insurance premium payments, co-payments, and deductibles. Sometimes, the aggregate costs of co-payments and deductibles are limited to an annual maximum "out-of-pocket" expense. A beneficiary's affluence or ability to afford these costs could influence both plan selection and service utilization. To allow for the effects of a beneficiary's ability to afford the costs of insurance premiums, co-payments, deductibles, and other costs of the selected plan, from the MCDC-supplied dataset, we use the predicted "median household income" or the predicted "median home value" of residents in the beneficiary's ZCTA as the surrogate for the beneficiary's financial resources.

Level of Education. The selection of a Medicare plan can be a daunting task. Beneficiaries have numerous choices for their coverage. Those choices include Medicare with no secondary coverage, Medicare with Medicaid as secondary coverage, Medicare with commercial insurance for secondary coverage, Medicare Advantage PPOs, and

Medicare Advantage HMOs. Retirees may have additional choices arranged by their former employers. There can be numerous insurer and plan selections within these choices, and varying costs and benefits schedules can create additional complexities. Much of this information exists on CMS' and MAOs' websites. Other means of information distribution to inform or entice enrollees include elaborate marketing campaigns and mailings of informational packets containing dozens of pages.

Further, there is a cadre of independent brokers and insurance agents willing to meet one-on-one with potential enrollees to provide additional information and education about insurance offerings and to sell the health insurance policies. Consequently, we consider one's level of education as a beneficiary attribute that may be a factor in plan choice and service utilization. To allow for the effects of a beneficiary's ability to navigate the complexities of plan choice and utilization, from the MCDC-supplied dataset, we select the predicted "percent of households having a bachelor's degree or more" in the beneficiary's ZCTA as the surrogate for the beneficiary's level of education.

4.6 Data sufficiency

Differences in data collection techniques for Traditional Medicare and Medicare Advantage beneficiaries pose certain challenges for researchers. One notable concern is dealing with multiple claims or accountings for a single medical event as a result of various issues involving claims processing and MAO data reporting. While there are potential remedies to refine the data and eliminate duplicative records, it can be a daunting and imperfect task. To avoid the possibility of duplicative counting of any service event, we consolidate records of all services in a category (inpatient, SNF, outpatient, home health, and carrier) with the same date when counting the number of services for individual beneficiaries. This is one method recommended by ResDAC as discussed in their workshops and contained in several of their training materials. For inpatient and skilled nursing, we count the number of distinctive discharge dates. For the outpatient, home health, and carrier categories, we count the dates when a patient receives a service. If multiple service records occur on the same date within the same category, the count is "one."

4.6.1 Data Correlation Test. Service count summaries for FFS beneficiaries are in the Master Beneficiary Summary File (MBSF), but comparable count summaries for HMO beneficiaries are not. Therefore, to test our counting method, we subjected the FFS results to a correlation test. We compared the summary counts that we tallied from each of the FFS categories to their counterparts found in the MBSF. The results (see Appendix J) gave us confidence in our counting methodology as demonstrated by the very high correlation for each service category (inpatient $r = 0.996$, *p-value* < .001; skilled nursing $r = 0.999$, *p-value* =<0.001; outpatient $r = 0.993$, *p-value* < 0.001; home health $r = 0.979$; *p-value* < 0.001; and carrier $r = 0.933$, p-value < 0.001). Given the acceptable correlations from the FFS service count summaries, we applied the same counting methodology to the HMO service events.

4.6.2 MAO Data Collection Processes. In our conversations with the Essence representatives, we inquired about their confidence in their encounter data reporting to CMS. They told us that significant investments are made in their data collection and reporting processes, and they have high confidence in the accuracy of their data. We received similar comments from the UHC representatives. While this is encouraging, we judge that further triangulation is required to verify the consistency between FFS and

HMO data. For example, primary data collection studies could be conducted to investigate how data are collected and reported by all MAOs. This would include examinations and tests of the processes and systems that exist between providers and MAOs, and MAOs and CMS, as well as confirmation of their data accuracy. Second, data accuracy should be verified by third party sources such as Medicare cost reports or reviews of financial and medical records by independent auditors. We are aware that CMS is engaged in some of these activities, and we are encouraged by reports that data accuracy continues to improve.

4.7 Statistical Analysis

We employ various analyses, including summary statistics, tests of differences in means, CHAID decision trees, and Poisson regressions to examine the data and test our hypotheses.

4.7.1 Units of Analysis. The units of analysis are (a) for total system utilization: per capita utilization for various medical services by type of coverage, and (b) for individual beneficiaries (patients), annual summaries of their utilization of medical services (inpatient, outpatient, carrier, home-health assistance, skilled nursing facility) counted by the number of dates with records related to a service or diagnosis rendered in the service category.

4.7.2 CHAID Decision Trees. Chi-square automatic interaction detection (CHAID) decision trees are useful in uncovering relationships between variables. For this portion of the study, we imported a SAS dataset into the IBM SPSS Statistics Version 26. The dataset contained values for each of 143 variables representing services utilization data derived from the CMS merged datasets for our study's normalized population. To examine their effect on the Medicare plan choice target variable, we selected various explanatory variables to represent the beneficiaries' characteristics (see Exhibit 14). The CHAID parameters were set for a minimum of 2,000 cases per node, significance levels of 0.01, utilization of the Pearson chi-square statistic, a maximum of 100 model iterations, and a tree depth of three. The purpose of the CHAID analysis is to cluster individuals with similar values of "target" or "independent" variables with consideration of possible nonlinear relationships and interactions between explanatory factors (independent variables). The clusters reveal predicted values (e.g., plan choice, services utilization) for beneficiary groups based on specific attributes such as age, race, or health status. Statistically significant differences in the predicted values for the explanatory variables will lend support to our hypotheses.

Exhibit 14. CHAID Tree Variables Used for Medicare Plan Choice Analysis

Explanatory (independent) variables

- Age – defined as the beneficiary's age at the end of the year
- Gender – male, female, other
- Race – White, Black, Hispanic, North American Native, Other
- Health status – represented by the Charlson Co-morbidity Index from inpatient ICD codes
- Access to doctors – number of doctors in the beneficiary's residence county
- Access to hospitals – value of 1, 2, or 3 to define the proximity of hospitals to the beneficiary's residence county
- Median home value – for the beneficiary's ZCAT
- Education – American Community Survey estimate of the % of bachelor degree or more households within the beneficiary's residence ZCAT

Target (dependent) variables

- Medicare Plan Choice

Results of this clustering of beneficiaries according to choice of Medicare plans are presented in Section 5.1

4.7.3 Tests of Difference in Means. Our interviews and field observations involving PCPs and MAOs inform us that many essential performance measures in the Medicare industry involve calculating utilization ratios to determine the mean service count per beneficiary for each service category. We use tests of differences in independent means (e.g., mean number of inpatient admissions per beneficiary) to assess the magnitudes and statistical significance of the variances in service utilization among the plan beneficiaries. Specifically, we compare the service rates per beneficiary for each of the five service categories (inpatient, skilled nursing, outpatient, home health, and carrier) for beneficiaries enrolled in Medicare Advantage (HMO) plans with those enrolled in Traditional Medicare (FFS) plans. We also examine differences between utilization rates by enrollees in four Medicare Advantage market leaders versus enrollees in FFS plans. These results are reported in Section 5.2.

4.7.4 Poisson Regression. Poisson regression is useful when analyzing the effects of multiple variables on a target variable expressed as a count. This method is helpful when predicting utilization rates (and estimated costs) attributable to a panel of beneficiaries assigned to a specific plan, hospital system, medical group, or individual practitioner. It also enables analysts to predict utilization changes driven by changing attributes (such as aging or health status) of the individuals in the group being evaluated. These types of analyses are critical in determining whether plans or providers should enter into or continue with risk-bearing contracts. Plans and providers presumably would prefer to forgo any situation where projected utilization (and costs) would outstrip the associated revenues. Also, for budgeting and legislative purposes, policymakers may wish to know the projected utilization and costs of services authorized under the Medicare program and its various plans.

Using SAS, we introduce 22 explanatory variables into our regression model and determine the statistical relevance of each variable for each of the five service categories (inpatient, skilled nursing, outpatient, home health, and carrier). The 22 variables and their origins are shown in Exhibit 15. We examine the resulting "full" models that contain all 22 variables and then employ backwards elimination to reduce each regression model to exclude any variable that does not show statistical significance on the margin (eliminating, at each stage, the variable with largest *p-value* > 0.01). Results of this analysis are presented in Section 5.3.

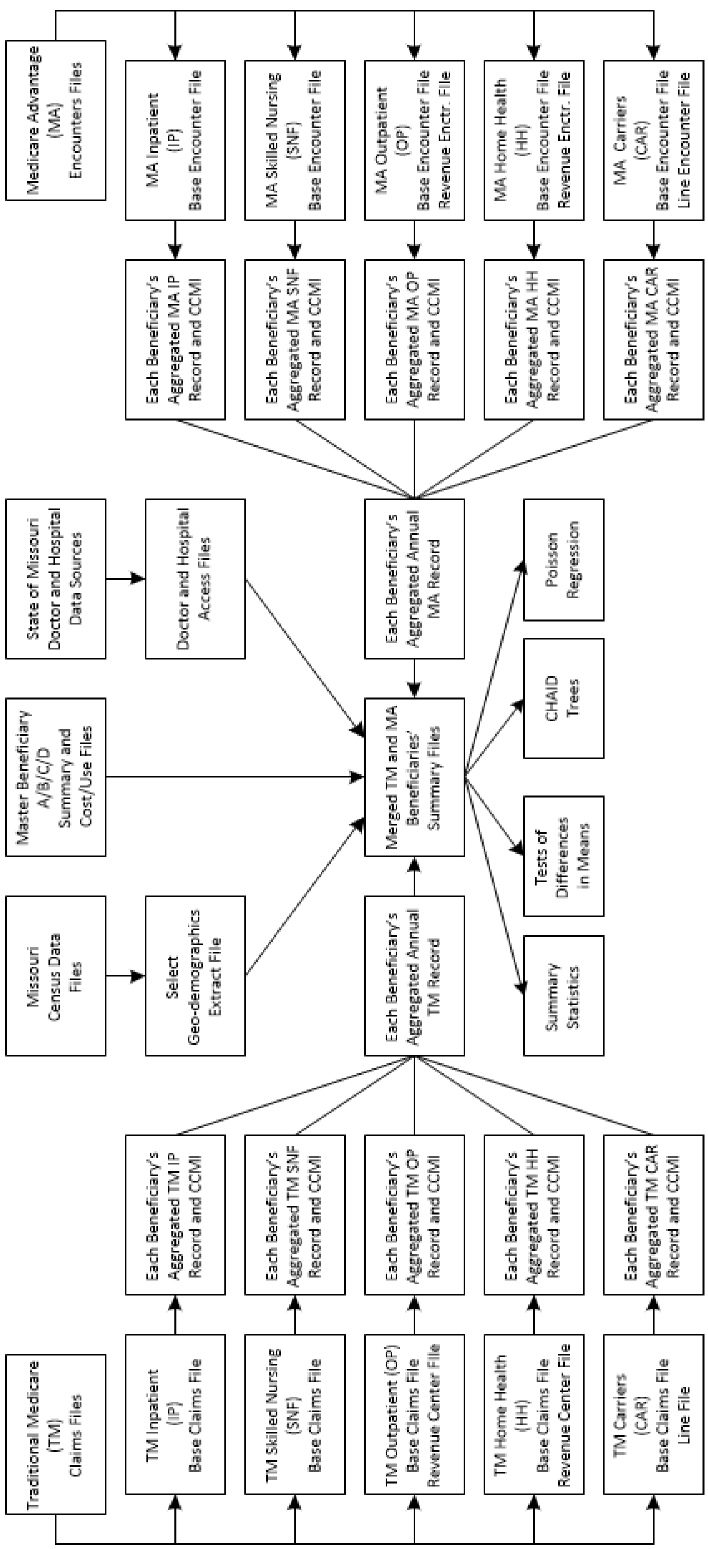
Exhibit 15. Poisson Regression Variables

Variable	Description
numipadmits	Inpatient admissions based on discharge dates
numOPsrvcevents	Outpatient service events
numOPsrvcrecs	Outpatient service records
numcarsrvcrecs	Carrier services
numCARdiagevents\	Carrier events with recorded diagnoses
numhhasrvcrecs	Home health service records
numsnfdiagevents	Skilled nursing events based on dates with recorded diagnoses
maxchscoreallser	Highest charlson score of all service categories
female	Gender selection from male, female, and other
HMOplan	Enrolled in HMO rather than FFS plan
yrendage	Beneficiary aged at year end
Black	Race variable sub-category
Hispanic	Race variable sub-category
Asian	Race variable sub-category
Other non-white	Race variable sub-category representing all races other than Black, Hispanic, and Asian
medianhouseeval	Zip code median house value expressed in $100,000 increments
zpctbachelorsormore	Zip code average percent households with bachelors degree or more
zpctmanprofoccs	Zip code average percent of households with managerial or professional employment
hospitalaccess1	Missouri counties having one or more hospitals
hospitalaccess2	Missouri counties without a hospital but having one ≤ 27 miles of county seat
hospitalaccess3	Counties without a hospital and with the nearest hospital being >27 miles from county seat
physiciansper1000	Average number of physicians per 1,000 beneficiaries in a county

Exhibit 15. Count variables such as discharges or service events represent annual amounts for an aggregated beneficiary record.

Data Summary. In Exhibit 16, we provide a diagram showing all of the sources of uses of data contained within this study.

Exhibit 16. Sources and Uses of Data



Note: CCMI = Charlson Co-morbidity Index

Chapter 5: Statistical Results

In this chapter, we discuss the effects of beneficiary characteristics on Medicare plan choice and service utilization. First, using CHAID decision trees, we construct clusters of individuals with the same propensity to choose one health plan versus another and examine the characteristics of individuals with which choice of plan is related. Second, we employ tests of differences in means to compare service utilization of beneficiaries enrolled in various Medicare Advantage (HMO) plans with those enrolled in the traditional Medicare (FFS) plan. Lastly, using Poisson regression, we study, for the different insurance plans, how the number of service encounters of each type depends upon beneficiary characteristics and other factors.

5.1 Plan Choice

To analyze Medicare plan choice, we present the results of several CHAID decision trees. We introduce into the models various beneficiary demographical attributes to determine their relationships to the beneficiary's Medicare Plan choice.

5.1.1 Beneficiary Characteristics. H1 states that the choice of Medicare insurance plan depends on the characteristics of beneficiaries, their access to doctors and hospitals, and their wealth and education. Our CHAID tree analyses support the hypothesis. In Exhibits 18 to 27, we present a series of CHAID decision trees with descriptions of the findings. The plan choice labels displayed in the output diagrams are a) the Traditional Medicare plan [indicated as "None," meaning not a Medicare Advantage plan], b) each of the four Medicare Advantage market share leaders based on their beneficiary enrollments [rankings are Essence #1, UHC #2, Humana #3, and Aetna #4], and c) the collection of all other Medicare Advantage plans [indicated as "Other"].

Age and Plan Choice. In Exhibit 17 and Table 15, we demonstrate the impact of a beneficiary's age on Medicare plans selection. This CHAID tree reveals five age clusters having differing plan selection results, and those results are highly statistically significant (p-value < 0.001, $X^2 = 1373.295$, $df = 20$). The youngest age cluster (Node 1, <=68.0, 69.3%) and the oldest age cluster (Node 5, >82.0, 69.6%) have a projected Traditional Medicare enrollment of approximately the same rate, which is greater than the other three age clusters. While the analysis does not explain why these results occur, we speculate that beneficiaries in the youngest age cluster have not yet decided to move from Traditional Medicare into an HMO plan. Further, we suspect that beneficiaries in the oldest age cluster may have less experience with HMOs than the other beneficiary groups, and, therefore, are likely to prefer the FFS plan option.

Exhibit 17. Age and Plan Choice

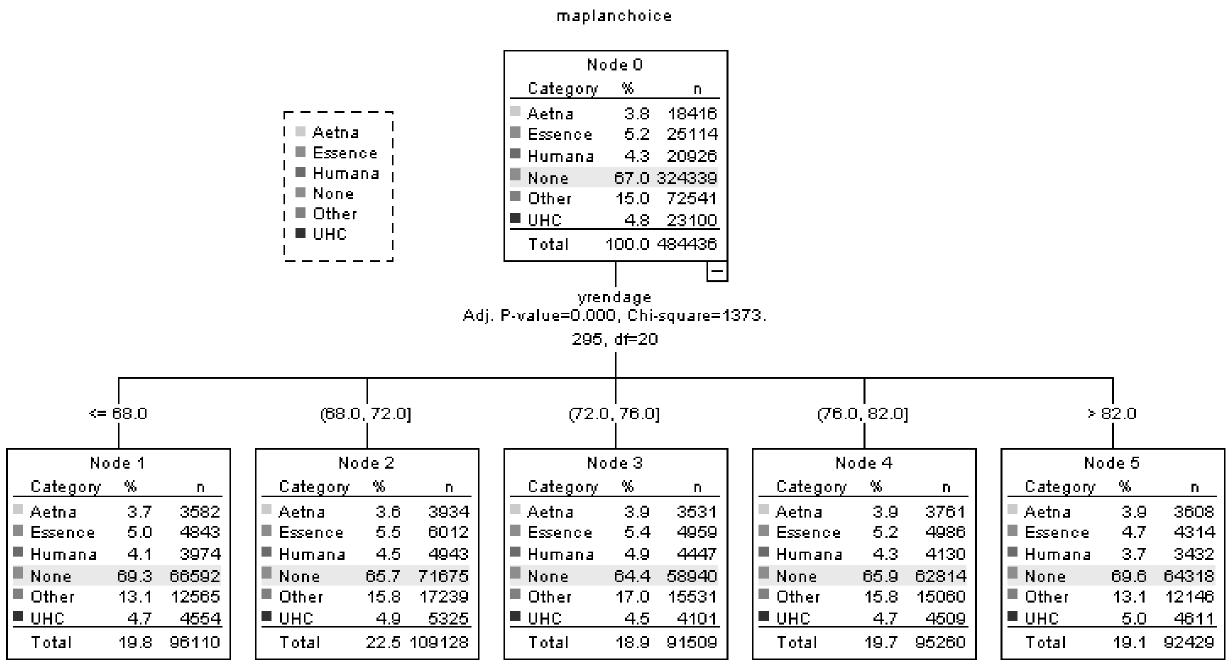


Table 15

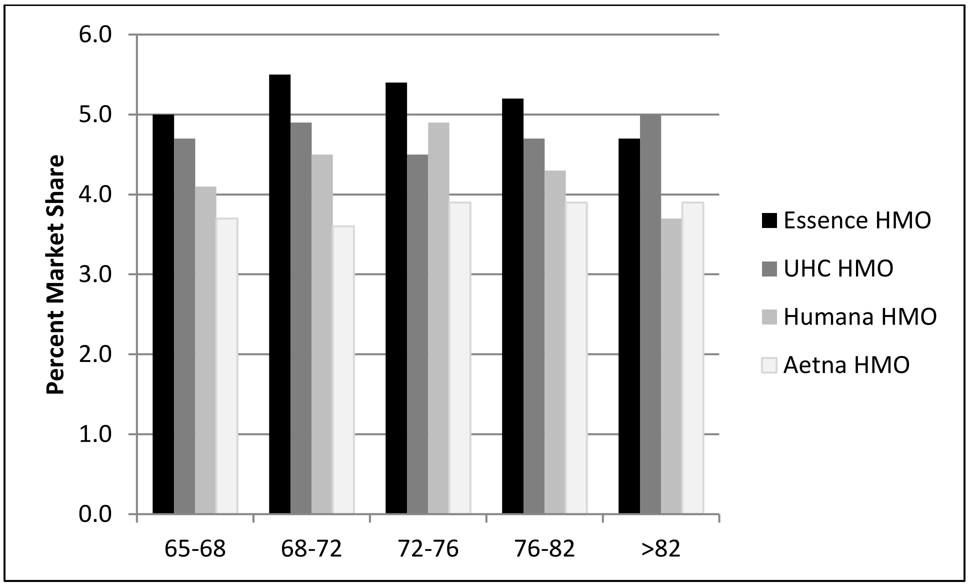
Percentage of Plan Members by Age Groups

	Age Clusters				
Plan Type	65-68	68-72	72-76	76-82	>82
FFS	69.3	65.7	64.4	65.9	69.6
All HMOs	30.6	34.3	35.7	33.9	30.4
Essence HMO	5.0	5.5	5.4	5.2	4.7
UHC HMO	4.7	4.9	4.5	4.7	5.0
Humana HMO	4.1	4.5	4.9	4.3	3.7
Aetna HMO	3.7	3.6	3.9	3.9	3.9
Other HMOs	13.1	15.8	17.0	15.8	13.1

Note: FFS plus ALL HMOS may not total to 100.0 due to rounding.

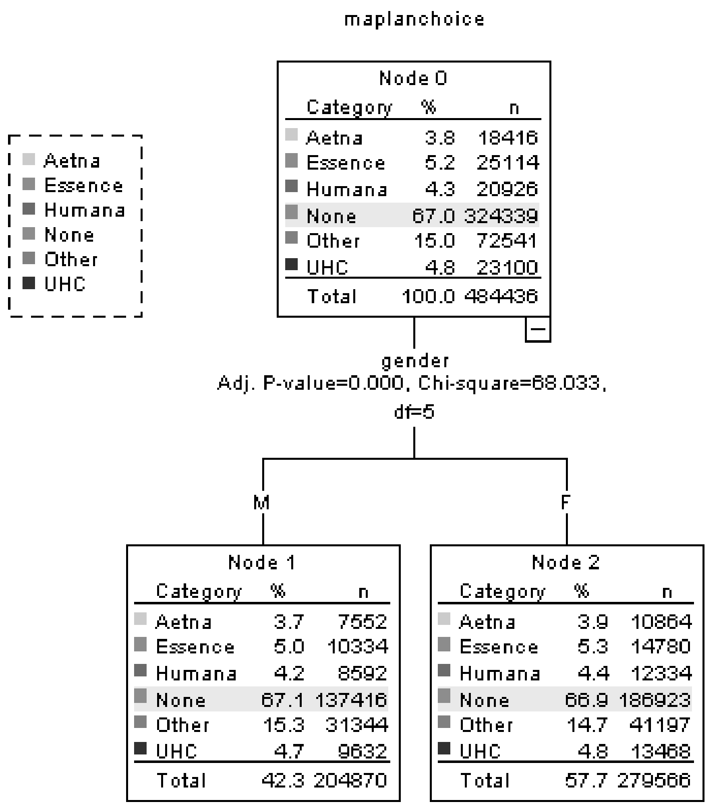
The distribution of choices among the top four HMO plans are consistent with published statistics in secondary sources; however, their market shares vary from cluster to cluster (see Exhibit 18). Further investigation of factors affecting choices of Medicare plans is left for future research, perhaps with nationwide scope.

Exhibit 18. Top HMO Plans' % Market Share by Age Cluster



Gender and Plan Choice. In Exhibit 19, the CHAID tree reveals that the two gender clusters (male, female) have differing plan selection results, and those results are statistically significant (p-value < 0.001, $\chi^2 = 69.033$, $df = 5$). However, the projected percentage of each gender's selection of the Traditional Medicare plan selection is only nominally different (male = 67.1%, female = 66.9%). We also note that the probable Medicare Plan selections for both genders are consistent with each plan's market share rankings.

Exhibit 19. Gender and Plan Choice



Race and Plan Choice. The CHAID tree in Exhibit 20 reveals five clusters based on the beneficiary's ethnicity (or race), and differences in choice of plan are highly statistically significant (p-value < 0.001, $\chi^2 = 5727.150$, $df = 20$). The "Black" race cluster shows a much lower probability of enrollment (51.8%) in the Traditional Medicare plan than the other race clusters. The other race clusters predict enrollment in Traditional Medicare from a low of 63.4% (Node 5, "Other") to a high of 73.4% (Node 4, "Unknown"). Nodes 1 and 2 represent 98% of the total population, and both nodes reflect a Medicare Advantage plan choice that is consistent with each plan's market share rankings. One area of future research is to understand why Black race beneficiaries are much more likely to enroll in HMOs than are other beneficiaries (see Exhibit 21). We also note the significantly higher percentage of Blacks' enrollment into Essence as compared to the other HMO plans. Are the Essence plan benefits as compared to other plans more appealing to Blacks? Compared to other plans, does Essence focus its marketing efforts more intentionally toward the Black population? Does Essence offer its plans in regions with higher than average Black populations? These and other questions could be explored with further research.

Exhibit 20. Race and Plan Choice

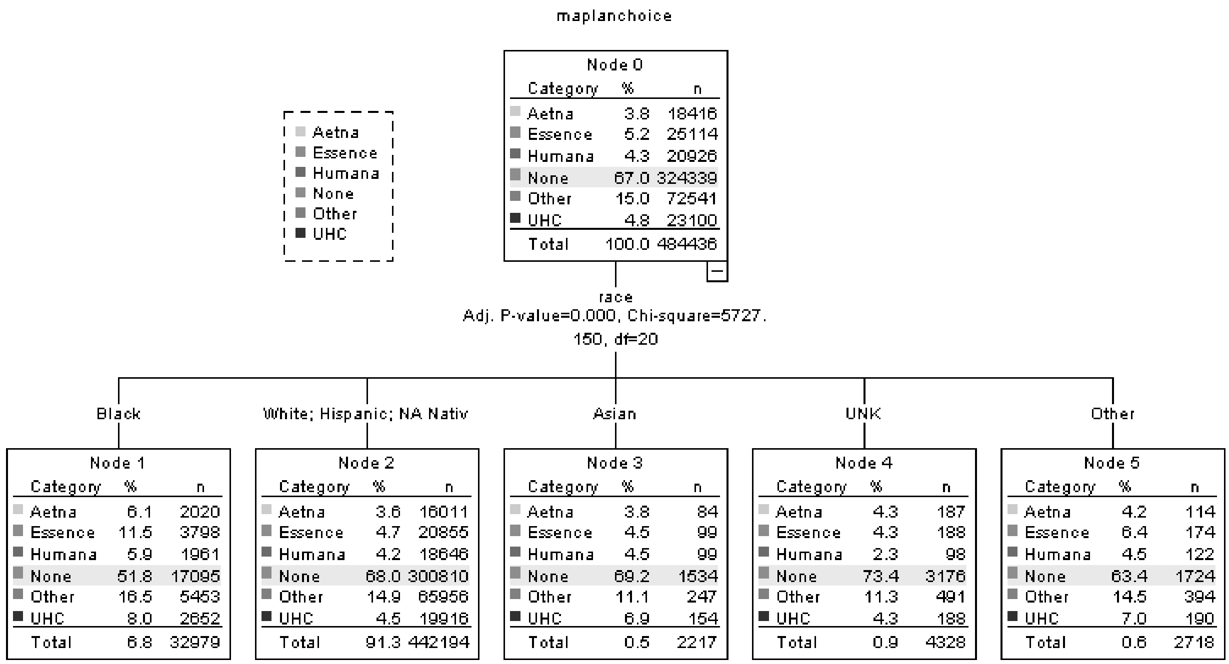
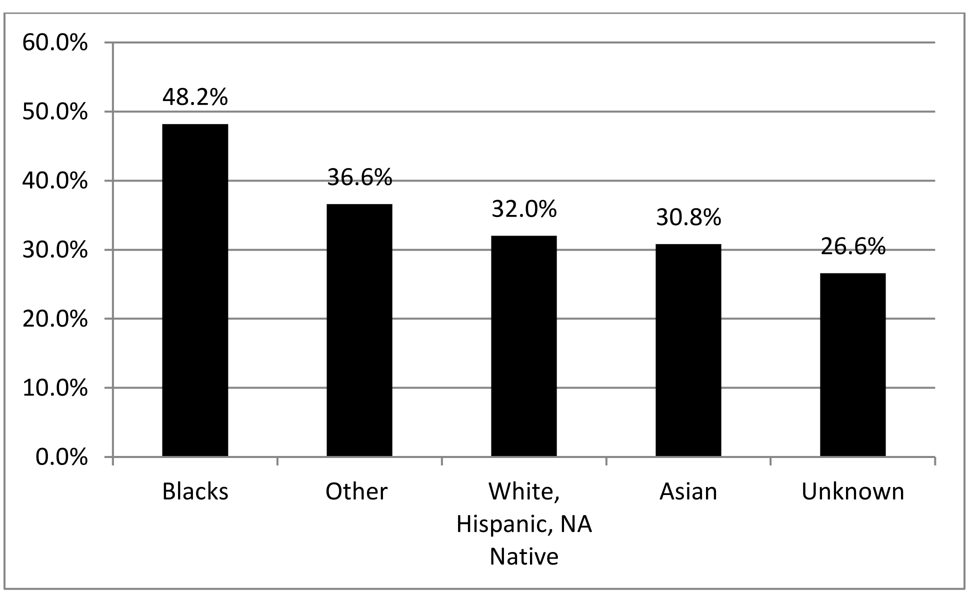


Exhibit 21. HMO Plan Choice by Race



Charlson Score and Plan Choice. In this analysis, the maximum Charlson score from all services categories was selected as the explanatory variable. In Exhibit 22, the CHAID tree contains six Charlson-score clusters. The difference in predicted plan selection for these clusters is highly statistically significant (p-value < 0.001, χ^2 = 3968.490, df = 25). The beneficiaries with the greatest predicted enrollment in Traditional Medicare are those with Charlson scores = 0 (Node 1, 69.9%). We note that a Charlson score = 0 indicates those beneficiaries who either did not have any recorded diagnosis codes in any service category during the year or their diagnosis codes not were severe enough to be included in the Charlson scoring algorithm. Those with Charlson scores > 5 show the lowest predicted Traditional Medicare enrollment. (Node 6, 59.7%). The tree suggests that higher Charlson scores associate with lesser Traditional Medicare enrollment, although the difference in Traditional Medicare enrollment between each score cluster is not dramatically different. We note that third place market leader Humana is predicted to have the highest enrollment of beneficiaries with Charlson scores = 0 (4.1%) while market leader Essence is predicted to have the highest enrollment of beneficiaries with Charlson scores > 5 (7.8%). Essence and UHC are predicted to extend their market share leads as Charlson scores increase (see Exhibit 22.)

Exhibit 22. Maximum Charlson Score and Plan Choice

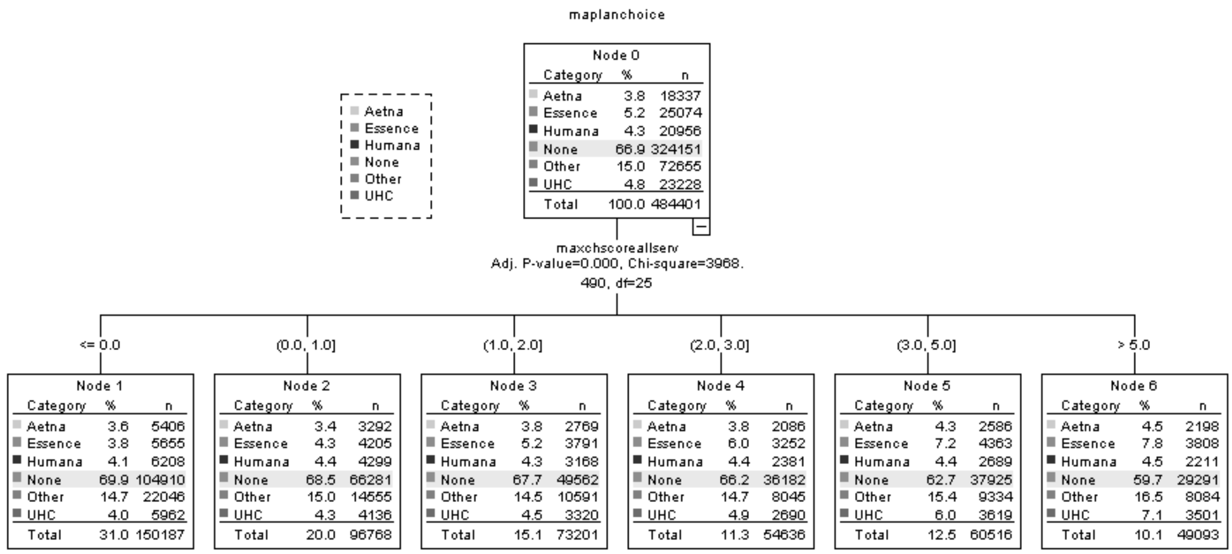
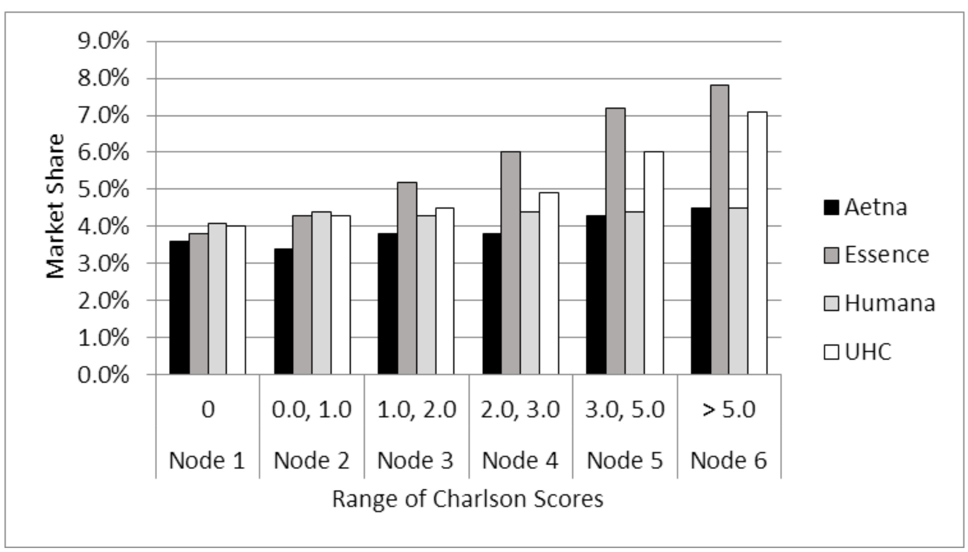
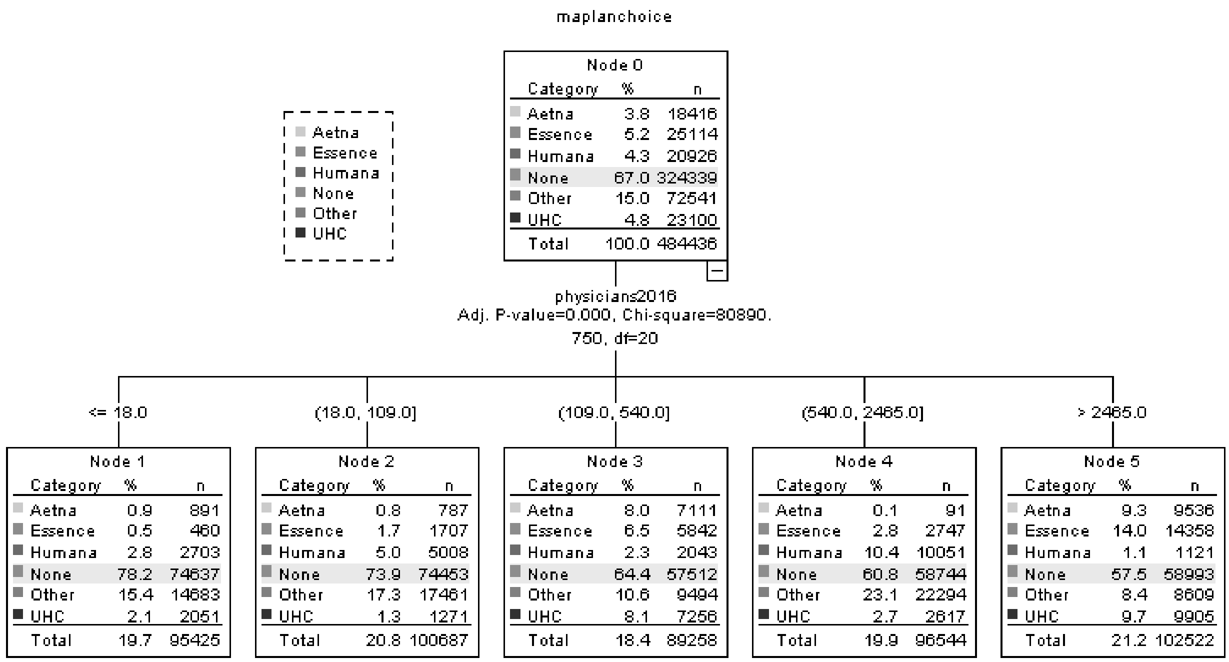


Exhibit 23. Plan Choice by Market Leaders and Maximum Charlson Score



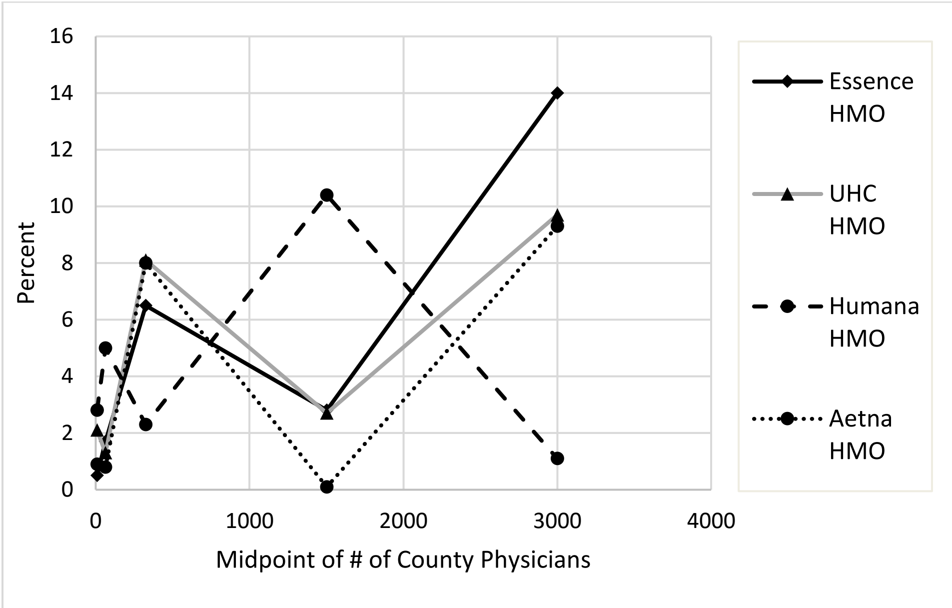
Physician Count and Plan Choice. The CHAID tree in Exhibit 23 reveals five physician count clusters having differing plan selection results, and those results are highly statistically significant (p-value < 0.001, $\chi^2 = 80890.750$, $df = 20$). Beneficiaries residing counties with 18 or fewer physicians (Node 1) have the highest probability of the FFS plan selection (78.2%). Because CMS has standards to assure adequate provider coverage, we suspect this result shows that beneficiaries in many counties have little to no access to HMO alternatives due to an insufficiency of physician coverage. In contrast, beneficiaries in counties with more than 2,465 physicians (Node 5) are the least likely to select Traditional Medicare (57.5%), and therefore most likely to select a Medicare Advantage plan. We also note that specific Medicare Advantage plan choices within each cluster are somewhat inconsistent compared to the individual plans' market share rankings.

Exhibit 24. Physician Count and Plan Choice



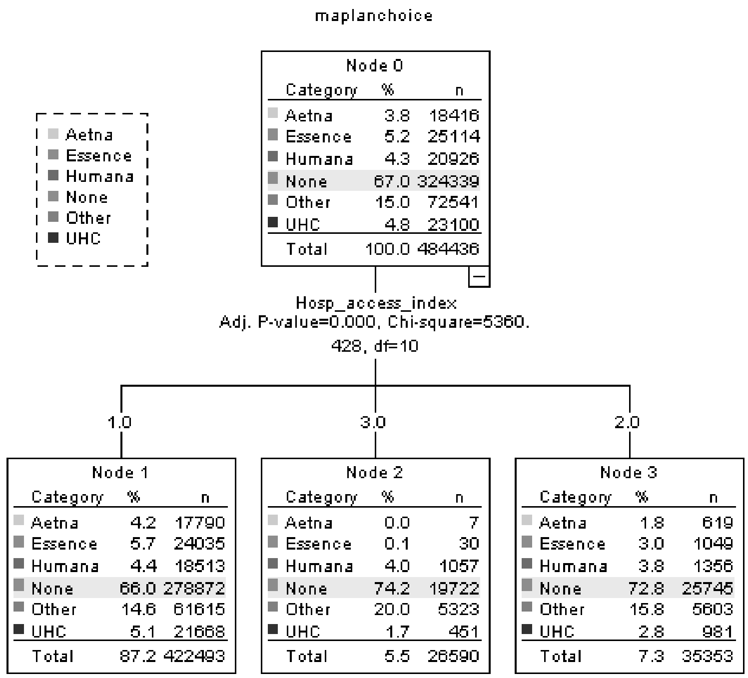
The graph displayed in Exhibit 24 shows the variances in beneficiary enrollment, by plan, relative to the midpoint of the number of physicians in the counties where those beneficiaries reside. Here we wonder what factors might be contributing to these variances. For example, does a plan with greater physician presence than others within the same county make that plan more attractive to beneficiaries? Do some plans have more effective marketing and recruitment campaigns in some counties than the other plans, resulting in higher enrollment numbers? Do some plans choose not to have a presence in some counties? These questions offer opportunities for additional research. Clearly, the degree of physician presence in a county impacts beneficiary plan choice.

Exhibit 25. % Enrollment by HMO Plan Based on County Physician Count



Hospital Access and Plan Choice. The CHAID tree in Exhibit 25 reveals all three hospital access code clusters, and the results are highly statistically significant (p-value < 0.001, $\chi^2 = 5360.428$, $df = 20$). Beneficiaries residing in counties most distant from a hospital (Node 3) show the highest probability of Traditional Medicare plan selection (74.2%). Because CMS has standards to assure that plans have adequate hospital coverage, we suspect this result is due to beneficiaries in many counties having little to no access to Medicare Advantage alternatives because of an insufficient hospital presence. In contrast, beneficiaries in counties with one or more hospitals (Node 1) are the least likely to select Traditional Medicare (66.0%), and, therefore, the most likely to select an HMO plan.

Exhibit 26. Hospital Access and Plan Choice



Median Home Value and Choice. In Exhibit 26, the CHAID tree reveals five child node median home value clusters of comparable populations having differing plan selection results, and those results are highly statistically significant (p-value < 0.001, χ^2 = 67,055.308, df = 20). Beneficiaries in regions with the projected lowest value homes (Node, 1, ≤ $96,800, 80.2%) are more likely to select the Traditional Medicare plan as compared to beneficiaries residing in regions having higher median home values. Beneficiaries in the regions with the projected highest median home values (Node 5, >$161,000, 59.2%) are less likely to select the Traditional Medicare plan as compared to other beneficiaries. Overall, the groupings indicate that Traditional Medicare plan selection is higher in areas with lower median home values. Also, the Medicare Advantage plan choices in each income cluster generally do not reflect the plans' market share rankings (see Exhibit 27). Future research could investigate this result to determine what factors are driving these variances. For example, if median home values are greater in urban and suburban areas as compared to rural areas, then it is likely that urban and suburban beneficiaries have more Medicare Advantage alternatives that offer greater attraction than Traditional Medicare.

Exhibit 27. Median Home Value and Plan Choice

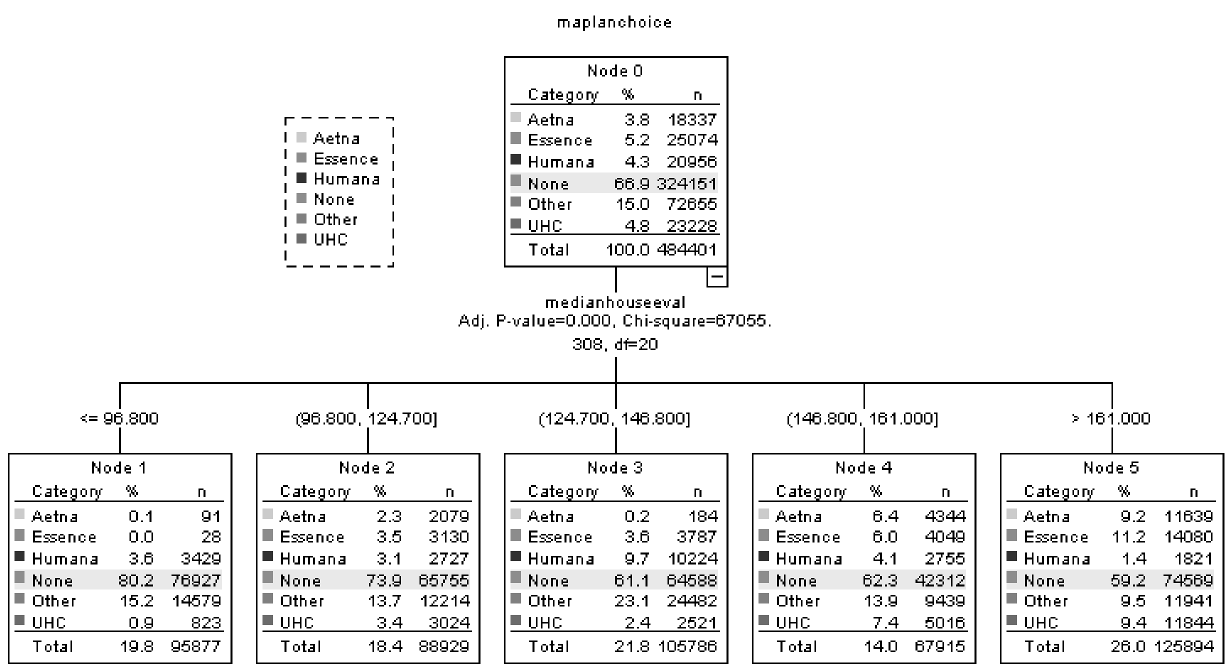
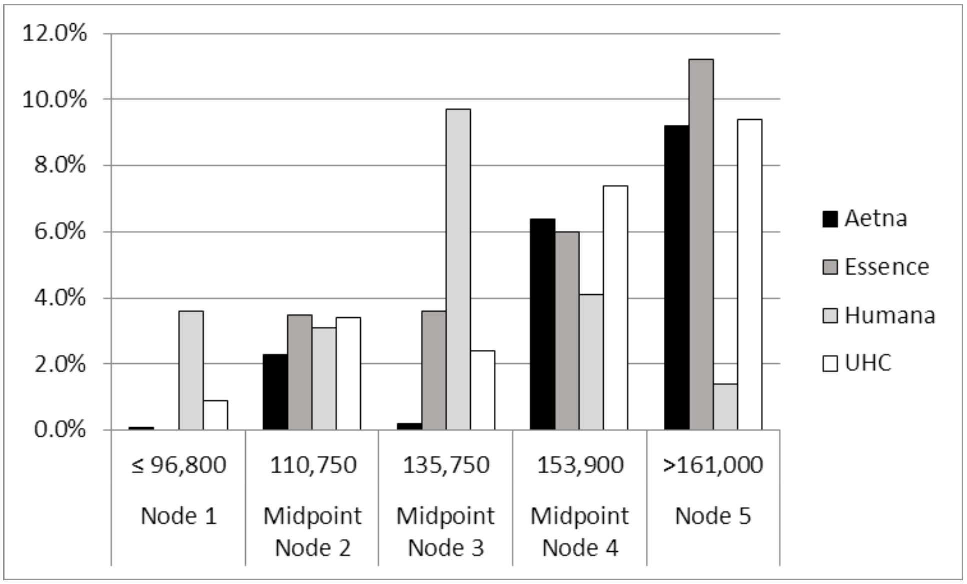


Exhibit 28. Plan Choice of Top HMOs by Median Home Value Cluster Midpoint



All Variables and Plan Choice. Lastly, we consider the implications of entering all eight variables into the CHAID tree model. The resulting tree contains three levels with 25 mutually exclusive clusters, making it unrealistic to display in this paper. Alternatively, in Appendix M, we offer the tree results in a tabular form. Here we summarize the results.

Five physician count clusters (number of physicians in a county) emerge as the level one child nodes and they are highly statistically significant (*p-value* < 0.001, $\chi^2 = 80560.808$, $df = 20$). Beneficiaries in the counties with the fewest physicians (Node 1, physician count ≤ 18) are most likely to enroll in the Traditional Medicare plan (78.1%). Beneficiaries in the counties with the most physicians (Node 5, physician count $> 2,465$) are least likely to enroll in the Traditional Medicare plan (57.5%). Nodes 2, 3, and 4 show a similarly consistent pattern. We conclude that beneficiaries residing in counties with fewer doctors have a higher probability of the Traditional Medicare plan selection, possibly due to the lesser availability of HMO plans.

At Level Two (where statistically significant variables attach to Level One nodes), hospital access emerges as a significant variable (Nodes 6 – 8) for counties where physician count is low (physician count $\leq$ 18). Median home value becomes statistically relevant, occupying four nodes (Nodes 12 -15) and representing beneficiaries residing in counties having a broad range of physician counts (Count = 18 to 2465). Maximium Charlson score occupies the final Level 2 clusters (Nodes 16 – 18) with significance for beneficiaries residing in high physician count counties (Count > 2465).

At Level Three (where statistically significant variables attach to Level Two nodes), education level (i.e., households with bachelors degree or more) is statistically relevant for several nodes (Nodes 19, 20, 23, 24, 25, and 26). Across the entire tree, the highest probability of Traditional Medicare plan choice (Node 11, 85.7%) resides with beneficiaries in counties having median home values ≤ $146,800 and a moderate presence of physicians (109 - 540). The lowest probability of Traditional Medicare plan choice (Node 12, 48.2%) resides with beneficiaries of residing in counties with median home values ranging from $146,800 to $161,000 and with a moderate presence of physicians (109 – 540). We find these results to be curious in that the highest and lowest likelihood of Traditional Medicare enrollment is distinguished only by the median home values in counties with the same physician presence (109 – 540). This is an opportunity for future research.

From this collection of CHAID trees, we conclude that Medicare plan choice is, indeed, related to the beneficiaries' demographical attributes and those attributes are statistically significant. For example, the findings imply that HMOs are less prevalent in rural communities (i.e., low physician count and low hospital access) and more prevalent in metropolitan areas (i.e., high physician count and high hospital access). This is likely due to CMS' mandated provider thresholds. Those who are in the youngest and oldest age clusters tend to enroll in the FFS plan more so than beneficiaries in the central clusters. Perhaps the youngest and the oldest beneficiaries have less familiarity with their Medicare HMO alternatives. Blacks are more likely to enroll in HMOs than are other races. Perhaps a higher percentage of Blacks (compared to non-Blacks) live in metropolitan areas where HMO plans are more plentiful than other areas. We also find that when all eight variables enter the model, only "gender" shows no statistical relationship to plan choice. Why isn't' there a difference? Why do median home values show some curious effects on plan choice? The data do not tell us "why" these results are predicted, but they do leave open the door for more research. Nevertheless, we can conclude that these variables, both singularly and combined, have differing effects on the beneficiaries' specific Medicare plan selections. These findings support our H1 that beneficiaries' attributes, proximity to hospitals and doctors, and levels of education and wealth are statistically associated with Medicare plan choices.

5.2 Service Utilization: Tests of Differences in Means

In this section, we present averages and percentiles for measures of service delivery derived from all 2016 transactional records for the study's population (see Table 10). Both H2 and H3 propose that plan choice impacts service utilization. To test H2, we look at service utilization for the FFS plan, all HMO plans combined, and for each of the four market leader HMOs. We find that beneficiaries in the HMO plans, including the top four market share plans, use fewer services in all service categories. Summary statistics are displayed in Table 16, followed by the detailed SAS outputs and summaries for each scenario, as shown in Exhibits 29 through 33.

Table 16

% Difference in Mean Utilization Per Beneficiary as Compared to FFS Plan

Service	All HMO	Essence	UHC	Humana	Aetna
Inpatient	-22%	-38%	-23%	-18%	-27%
Outpatient	-46%	-59%	-50%	-46%	-44%
Carrier	-8%	-11%	-5%	-16%	-12%
Home Health	-47%	-77%	-66%	-13%	-39%
Skilled Nursing	-29%	-47%	-23%	-25%	-26%

5.2.1 Overall differences for the study population. For the study's normalized sample population (n = 646,230), in every service category, the mean service utilization per HMO beneficiary is less than the mean service utilization per FFS beneficiary, and the differences are statistically significant. These results are displayed in Exhibit 29.

Exhibit 29. Differences in FFS and HMO Events per Beneficiary

Differences in Average Number of Events between HMO (MA) Sample and FFS Sample

Service Metric	No. FFS Beneficiaries	FFS Mean	FFS Std. Dev.	No. MA Beneficiaries	HMO Mean	HMO Std. Dev.	Difference in Means	Pct. Diff in Means	t-test value	One-tail P-value	Two-tail P-value
1:Inpatient Dschg	432,765	0.279	0.7563	213,465	0.217	0.6645	-0.062	-22.1	-33.5	.0000	.0000
2:Outpatient Srvc	432,765	8.364	12.8055	213,465	4.551	7.4465	-3.813	-45.6	-150.9	.0000	.0000
3:Outpatient Diag	432,765	6.035	7.2894	213,465	3.863	5.4614	-2.172	-36.0	-134.0	.0000	.0000
4:Carrier Srvc	432,765	46.435	48.6823	213,465	42.781	42.4304	-3.654	-7.9	-31.0	.0000	.0000
5:Carrier Diag	432,765	15.676	14.6507	213,465	13.743	12.8403	-1.933	-12.3	-54.3	.0000	.0000
6:HHA Srvc	432,765	1.512	7.4825	213,465	0.803	4.8174	-0.708	-46.9	-45.9	.0000	.0000
7:HHA Diag	432,765	0.095	0.3553	213,465	0.184	1.0456	0.088	92.4	37.9	.0000	.0000
8:SNF Diag	432,765	0.174	1.0294	213,465	0.075	0.4538	-0.099	-57.0	-53.8	.0000	.0000
9:SNF Dschrg	432,765	0.073	0.3563	213,465	0.052	0.3039	-0.021	-28.5	-24.4	.0000	.0000

The service category counts appear in lines 1, 2, 4, 6, and 9.

Inpatient. Inpatient discharges are lower for the HMO beneficiaries by 62 per 1,000 enrollees (22% lower), and the difference is highly statistically significant (*t-test* = -33.5, *p- value* < 0.001).

Outpatient. Outpatient services are lower for the HMO beneficiaries by 3,813 per 1,000 enrollees (46% lower) and the difference is highly statistically significant (*t-test* = -150.9, *p-value* < 0.001).

Carrier. Carrier services are lower for HMO beneficiaries by 3,654 per 1,000 enrollees (8% lower), and the difference is highly statistically significant (*t-test* = -31.0, *p-value* < 0.001).

Home health. Home health services are lower for HMO beneficiaries by 709 per 1,000 (47% lower) and the difference is highly statistically significant (*t-test* = -45.9, *p-value* < 0.001).

SNF. SNF discharges are lower for HMO beneficiaries by 21 per 1,000 enrollees (29% lower), and the difference is statistically significant (*t-test* = -24.4, *p-value* < 0.001).

5.2.2 MAO Variances. We also produced comparative statistics for each of the top four MAOs (by market share) based on each MAO's total beneficiary count. Collectively, they account for 54.7% of the Medicare Advantage study population. In every service category, the mean service utilization per HMO beneficiary derived from transactional data is less than the mean service utilization per FFS beneficiary. The differences are statistically significant.

Essence. Based on its beneficiary count (n = 33,472) within the study's Medicare Advantage population, this MAO holds the lead market position with a 15.7% share. The Essence results are displayed in Exhibit 30.

Exhibit 30. Differences in FFS and Essence Events per Beneficiary

Differences in Average Number of Events between HMO (MA) Sample and FFS Sample
For Essence Healthcare Part C Contract H2610

Service Metric	No. FFS Beneficiaries	FFS Mean	FFS Std. Dev.	No. MA Beneficiaries	HMO Mean	HMO Std. Dev.	Difference in Means	Pct. Diff in Means	t-test value	One-tail P-value	Two-tail P-value
1:Inpatient Dschg	432,765	0.279	0.7563	33,472	0.172	0.5472	-0.107	-38.2	-33.3	.0000	.0000
2:Outpatient Srvc	432,765	8.364	12.8055	33,472	3.454	6.1036	-4.910	-58.7	-127.1	.0000	.0000
3:Outpatient Diag	432,765	6.035	7.2894	33,472	2.832	4.0976	-3.203	-53.1	-128.2	.0000	.0000
4:Carrier Srvc	432,765	46.435	48.6823	33,472	41.443	37.6958	-4.992	-10.7	-22.8	.0000	.0000
5:Carrier Diag	432,765	15.676	14.6507	33,472	12.650	11.3134	-3.026	-19.3	-46.0	.0000	.0000
6:HHA Srvc	432,765	1.512	7.4825	33,472	0.343	2.4611	-1.169	-77.3	-66.4	.0000	.0000
7:HHA Diag	432,765	0.095	0.3553	33,472	0.079	0.5245	-0.017	-17.7	-5.8	.0000	.0000
8:SNF Diag	432,765	0.174	1.0294	33,472	0.041	0.2655	-0.133	-76.4	-62.4	.0000	.0000
9:SNF Dschrg	432,765	0.073	0.3563	33,472	0.038	0.2427	-0.034	-47.2	-24.0	.0000	.0000

The service category counts are shown in lines 1, 2, 4, 6, and 9.

Inpatient. Inpatient discharges are fewer for the Essence beneficiaries by 107 per 1,000 enrollees (38% lower), and the difference is highly statistically significant (*t-test* = -33.3, *p-value* < 0.001).

Outpatient. Outpatient services are fewer for the Essence beneficiaries by 4,910 per 1,000 enrollees (59% lower) and the difference is highly statistically significant (*t-test* = -127.1, *p-value* < 0.001).

Carrier. Carrier services are fewer for HMO beneficiaries by 4,992 per 1,000 enrollees (11% lower), and the difference is highly statistically significant (*t-test* = -22.8, *p value* < 0.001).

Home health. Home health services are fewer for Essence beneficiaries by 1,169 per 1,000 (77% lower) and the difference is highly statistically significant (*t-test* = -66.4, *p-value* < 0.001).

SNF. SNF discharges are fewer for Essence beneficiaries by 35 per 1,000 enrollees (47% lower) and the difference is statistically significant (*t-test* = -24.0, *p-value* < 0.001).

United Healthcare (UHC). Based on its beneficiary count (n = 30,764) within the study's Medicare Advantage population, this MAO holds the second place market position with a 14.4% share. UHC results are displayed in Exhibit 31.

Exhibit 31. Differences in FFS and UHC Events per Beneficiary

Differences in Average Number of Events between HMO (MA) Sample and FFS Sample
For United Healthcare Part C Contract H2654

Service Metric	No. FFS Beneficiaries	FFS Mean	FFS Std. Dev.	No. MA Beneficiaries	HMO Mean	HMO Std. Dev.	Difference in Means	Pct. Diff in Means	t-test value	One-tail P-value	Two-tail P-value
1:Inpatient Dschg	432,765	0.279	0.7563	30,764	0.215	0.6437	-0.065	-23.1	-16.8	.0000	.0000
2:Outpatient Srvc	432,765	8.364	12.8055	30,764	4.199	5.2770	-4.165	-49.8	-116.2	.0000	.0000
3:Outpatient Diag	432,765	6.035	7.2894	30,764	4.171	5.2021	-1.863	-30.9	-58.9	.0000	.0000
4:Carrier Srvc	432,765	46.435	48.6823	30,764	44.138	45.0986	-2.297	-4.9	-8.6	.0000	.0000
5:Carrier Diag	432,765	15.676	14.6507	30,764	13.074	12.1374	-2.602	-16.6	-35.8	.0000	.0000
6:HHA Srvc	432,765	1.512	7.4825	30,764	0.516	2.5153	-0.995	-65.9	-54.4	.0000	.0000
7:HHA Diag	432,765	0.095	0.3553	30,764	0.224	1.0790	0.129	134.8	20.8	.0000	.0000
8:SNF Diag	432,765	0.174	1.0294	30,764	0.087	0.5014	-0.087	-49.9	-26.7	.0000	.0000
9:SNF Dschrg	432,765	0.073	0.3563	30,764	0.056	0.3068	-0.017	-23.3	-9.3	.0000	.0000

The service category counts appear in lines 1, 2, 4, 6, and 9.

Inpatient. Inpatient discharges are fewer for the UHC beneficiaries by 64 per 1,000 enrollees (23% lower), and the difference is highly statistically significant (*t-test* = -16.8, *p-value* < 0.001).

Outpatient. Outpatient services are fewer for the UHC beneficiaries by 4,165per 1,000 enrollees (50% lower) and the difference is highly statistically significant (*t-test* = -116.2, *p- value* < 0.001).

Carrier. Carrier services are fewer for UHC beneficiaries by 2,297 per 1,000 enrollees (5% lower), and the difference is statistically significant (*t-test* = -8.6, *p-value* < 0.001).

Home health. Home health services are fewer for UHC beneficiaries by 996 per 1,000 (66% lower) and the difference is highly statistically significant (*t-test* = -54.4, *p-value* < 0.001).

SNF. SNF services are fewer for UHC beneficiaries by 17 per 1,000 enrollees (23.3% lower) and the difference is statistically significant (*t-test* = -9.3, *p-value* < 0.001).

Humana. Based on its beneficiary count (n = 27,930) within the study's Medicare Advantage population, this MAO holds the third-place market position with a 13.1% share. Humana results are displayed in Exhibit 32.

Exhibit 32. Differences in Number of FFS and Humana Events per Beneficiary

Differences in Average Number of Events between HMO (MA) Sample and FFS Sample
For Humana Part C Contract H2649

Service Metric	No. FFS Beneficiaries	FFS Mean	FFS Std. Dev.	No. MA Beneficiaries	HMO Mean	HMO Std. Dev.	Difference in Means	Pct. Diff in Means	t-test value	One-tail P-value	Two-tail P-value
1:Inpatient Dschg	432,765	0.279	0.7563	27,930	0.229	0.6637	-0.050	-17.9	-12.1	.0000	.0000
2:Outpatient Srvc	432,765	8.364	12.8055	27,930	4.535	8.2821	-3.830	-45.8	-71.9	.0000	.0000
3:Outpatient Diag	432,765	6.035	7.2894	27,930	3.610	5.6584	-2.424	-40.2	-68.1	.0000	.0000
4:Carrier Srvc	432,765	46.435	48.6823	27,930	39.081	37.3735	-7.354	-15.8	-31.2	.0000	.0000
5:Carrier Diag	432,765	15.676	14.6507	27,930	13.500	12.7136	-2.176	-13.9	-27.5	.0000	.0000
6:HHA Srvc	432,765	1.512	7.4825	27,930	1.312	6.4810	-0.200	-13.2	-4.9	.0000	.0000
7:HHA Diag	432,765	0.095	0.3553	27,930	0.198	1.2909	0.103	107.4	13.2	.0000	.0000
8:SNF Diag	432,765	0.174	1.0294	27,930	0.081	0.4632	-0.093	-53.5	-29.3	.0000	.0000
9:SNF Dschrg	432,765	0.073	0.3563	27,930	0.054	0.2965	-0.018	-25.3	-9.9	.0000	.0000

The service category counts appear in lines 1, 2, 4, 6, and 9.

Inpatient. Inpatient discharges are fewer for the Humana beneficiaries by 50 per 1,000 enrollees (18% lower), and the difference is statistically significant (*t-test* = -12.1, *p-value* < 0.001).

Outpatient. Outpatient services are fewer for the Humana beneficiaries by 3,829 per 1,000 enrollees (46% lower) and the difference is highly statistically significant (*t-test* = -71.9, *p-value* < 0.001).

Carrier. Carrier services are fewer for Humana beneficiaries by 7,354 per 1,000 enrollees (16% lower), and the difference is statistically significant (*t-test* = -31.2, *p-value* < 0.001).

Home health. Home health services are fewer for Humana beneficiaries by 200 per 1,000 (13% lower) and the difference is statistically significant (*t-test* = -4.9, *p-value* < 0.001).

SNF. SNF services are fewer for Humana beneficiaries by 19 per 1,000 enrollees (25% lower) and the difference is statistically significant (*t-test* = -9.9, *p-value* < 0.001).

Aetna. Based on its beneficiary count (n = 24,538) within the eligible population, this MAO holds the #4 MA market position with an 11.5% share of the sample population. Aetna results are displayed in Exhibit 33.

Exhibit 33. Differences in Number of FFS and Aetna Events per Beneficiary

Differences in Average Number of Events between HMO (MA) Sample and FFS Sample
For Aetna Part C Contract H2663

Service Metric	No. FFS Beneficiaries	FFS Mean	FFS Std. Dev.	No. MA Beneficiaries	HMO Mean	HMO Std. Dev.	Difference in Means	Pct. Diff in Means	t-test value	One-tail P-value	Two-tail P-value
1:Inpatient Dschg	432,765	0.279	0.7563	24,538	0.204	0.6813	-0.076	-27.1	-16.8	.0000	.0000
2:Outpatient Srvc	432,765	8.364	12.8055	24,538	4.716	8.0783	-3.648	-43.6	-66.2	.0000	.0000
3:Outpatient Diag	432,765	6.035	7.2894	24,538	3.580	5.0286	-2.455	-40.7	-72.3	.0000	.0000
4:Carrier Srvc	432,765	46.435	48.6823	24,538	40.703	39.0370	-5.732	-12.3	-22.0	.0000	.0000
5:Carrier Diag	432,765	15.676	14.6507	24,538	14.028	12.5928	-1.648	-10.5	-19.8	.0000	.0000
6:HHA Srvc	432,765	1.512	7.4825	24,538	0.916	5.2029	-0.596	-39.4	-17.0	.0000	.0000
7:HHA Diag	432,765	0.095	0.3553	24,538	0.179	0.9109	0.083	87.2	14.3	.0000	.0000
8:SNF Diag	432,765	0.174	1.0294	24,538	0.066	0.4200	-0.108	-62.1	-34.9	.0000	.0000
9:SNF Dschrg	432,765	0.073	0.3563	24,538	0.054	0.3506	-0.019	-25.8	-8.2	.0000	.0000

The service category counts appear in lines 1, 2, 4, 6, and 9.

Inpatient. Inpatient discharges are fewer for the Aetna beneficiaries by 75 per 1,000 enrollees (27% lower), and the difference is statistically significant (*t-test* = -16.8, *p-value* < 0.001).

Outpatient. Outpatient services are fewer for the Aetna beneficiaries by 3,648 per 1,000 enrollees (44% lower) and the difference is highly statistically significant (*t-test* = -66.2, *p-value* < 0.001).

Carrier. Carrier services are fewer for Aetna beneficiaries by 5,732 per 1,000 enrollees (12% lower), and the difference is highly statistically significant (*t-test* = -22.0, *p value* < 0.001).

Home health. Home health services are fewer for Aetna beneficiaries by 596 per 1,000 (39% lower) and the difference is highly statistically significant (*t-test* = -17.0, *p-value* < 0.001).

SNF. SNF services are fewer for Aetna beneficiaries by 19 per 1,000 enrollees (26% lower) and the difference is statistically significant (*t-test* = -8.2, *p-value* < 0.001).

5.2.3. Other comments. Under CMS requirements, the HMOs are required to offer benefits that are the same as or comparable to Traditional Medicare; however, with CMS approval, the HMOs may also enhance those benefits. For example, many HMOs offer the “Silver Sneakers” program that allows beneficiaries to obtain memberships at fitness clubs at little to no cost. Some HMOs enhance their prescription drug benefits by lowering co-payments, placing higher cost drugs into lower co-payment tiers, and including drugs that are not part of the Traditional Medicare authorized formulary. HMOs plans vary in their annual maximum out-of-pocket costs, deductibles, and co-payments. Furthermore, HMOs plans are not all available in all areas (i.e., counties), nor do they all have the same networks of providers. All of these and other factors could potentially affect the amount and mix of services received by the beneficiaries. It is possible to gather data from third party sources to complement the CMS data and make comparisons of the plans’ structures and operations. Accordingly, there are several opportunities to initiate research that makes a deeper dive into the effects of plan differences on services utilization, mix, and costs.

5.2.4 Comparative totals. One potential and significant plan difference is the presence and proliferation of RB PCPs. To test H3, we compare Essence HMO (the plan with known RB PCPs) results with all other plans. In Table 17, we present the side-by-side comparisons of summary statistics expressed in service counts per thousand beneficiaries for each of the plans.

Table 17

Service Counts per Thousand Beneficiaries in Sample Population

Services categories	FFS (TM)	All HMO (MA)	Essence	UHC	Humana	Aetna
Inpatient discharges	279	217	172	215	229	204
Outpatient service dates	8,364	4,551	3,454	4,199	4,535	4,716
Carrier service dates	46,435	42,781	41,443	44,138	39,081	40,703
Home health service dates	1,512	803	343	516	1,312	916
Skilled nursing discharges	73	52	38	56	54	54

We note that market leader Essence has the smallest service count per thousand beneficiaries of every plan in every category excepting Carrier services. This finding suggests that the presence of RB PCPs serving as medical gatekeepers may be a statistically relevant factor in interpreting the utilization variances of beneficiaries from differing plans.

Lastly, in Exhibit 34, we show per-beneficiary service usage for the top four HMOs relative to FFS beneficiaries. Again, we note that beneficiaries in all four HMO plans utilize fewer services than their FFS counterparts, and Essence ranks lowest in all categories excepting carrier services.

Exhibit 34. Relative Service Utilization for Top 4 HMOs vs. FFS

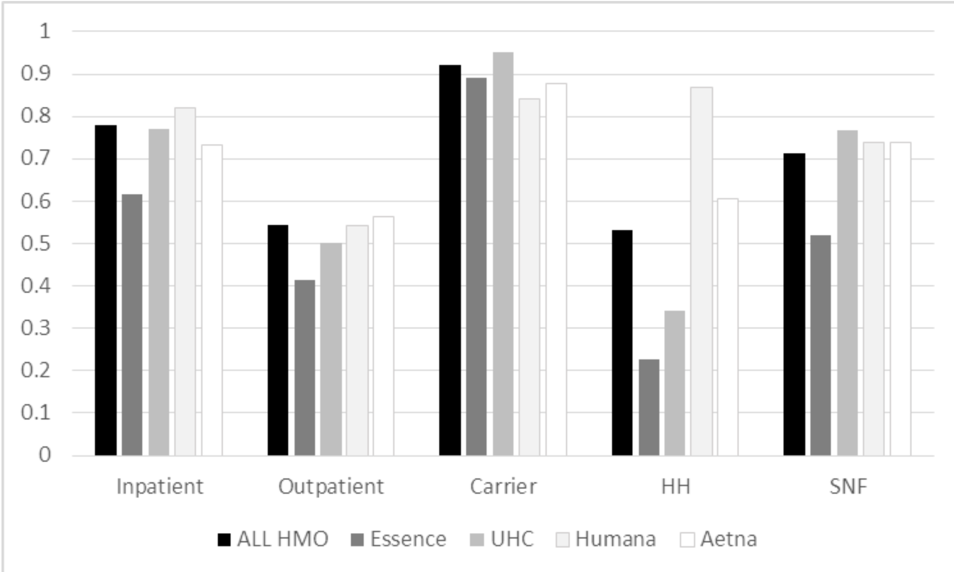


Exhibit 34. For relative comparisons, FFS = 1.

We do not know the extent to which HMO plans other than Essence engage RB PCPs. Consequently, while this evidence offers support of H3, ultimately, it is inconclusive. In future research, there is an opportunity to explore in greater detail the utilization patterns of beneficiaries assigned to the specific PCPs in the Essence plan. Comparing those results to similar beneficiary populations in the FFS plan and other HMO plans may reveal relevant variances that lend more support to H3.

5.3 Service Utilization: CHAID Decision Trees

The tests of differences in means are useful in examining summary statistics, but they do not consider the effects of multiple variables. To initiate our investigation of these effects, we constructed two CHAID decision trees to determine if any of the eight explanatory variables have an effect on inpatient utilization or outpatient utilization. The eight variables are shown in Exhibit 35.

Exhibit 35. CHAID Decision Tree Variables

Beneficiary Traits
- Race
- Gender
- Age at year-end
- Charlson scores

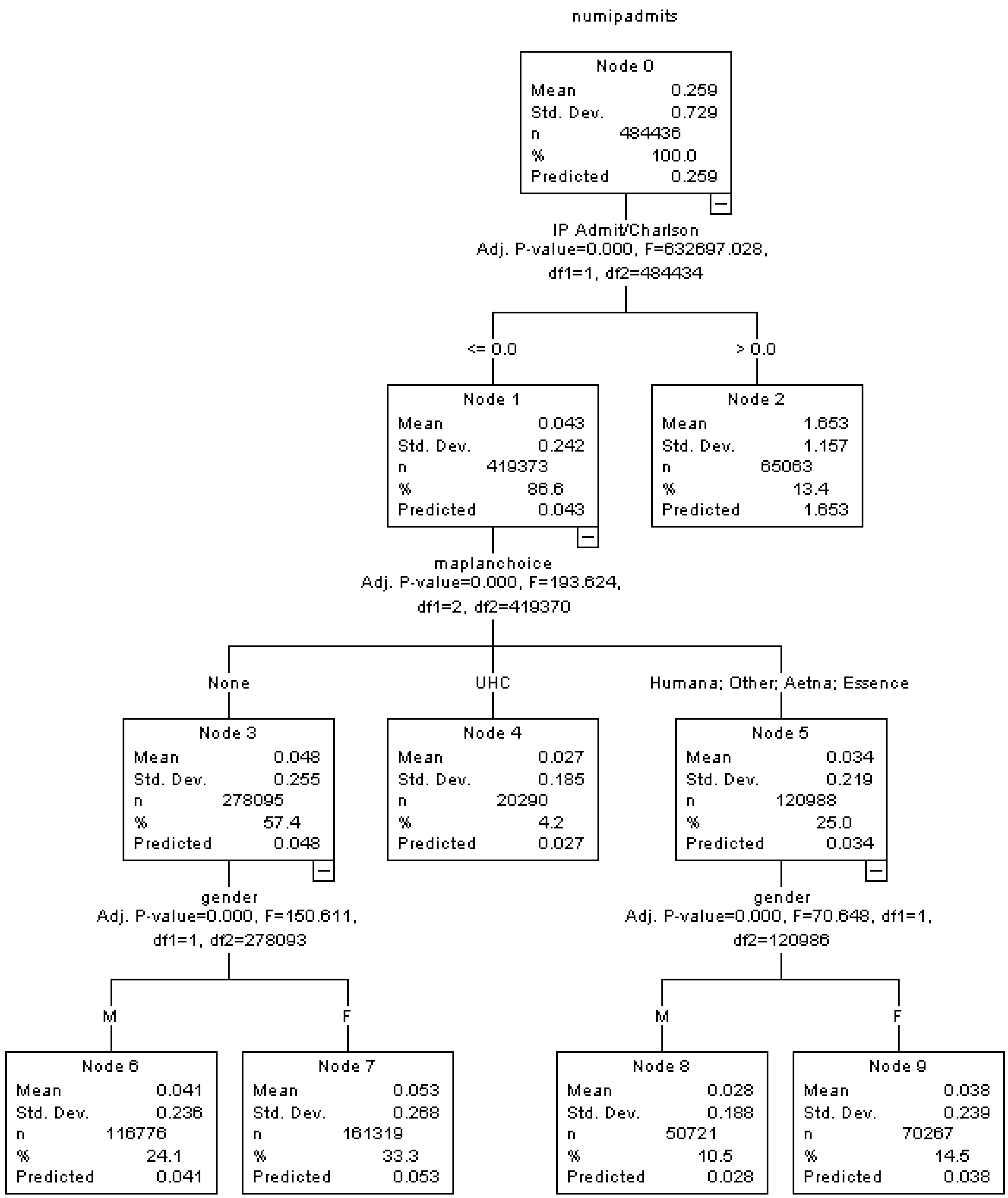
Beneficiary Access to Providers
- Proximity to hospitals based on county of residence
- Count of physicians in county of residence

Other
- Median home value in residence ZCAT
- % of households with a bachelors degree or more in residence ZCAT
- Beneficiary's Medicare plan choice

The inclusion of all eight variables results in a very large CHAID tree with numerous clusters, thus making interpretation difficult. Also, some clusters represent very small populations that contribute little to the analysis. Therefore, to reduce the number of clusters in our model, we adjusted the CHAID parameter to require a minimum of 20,000 records per cluster.

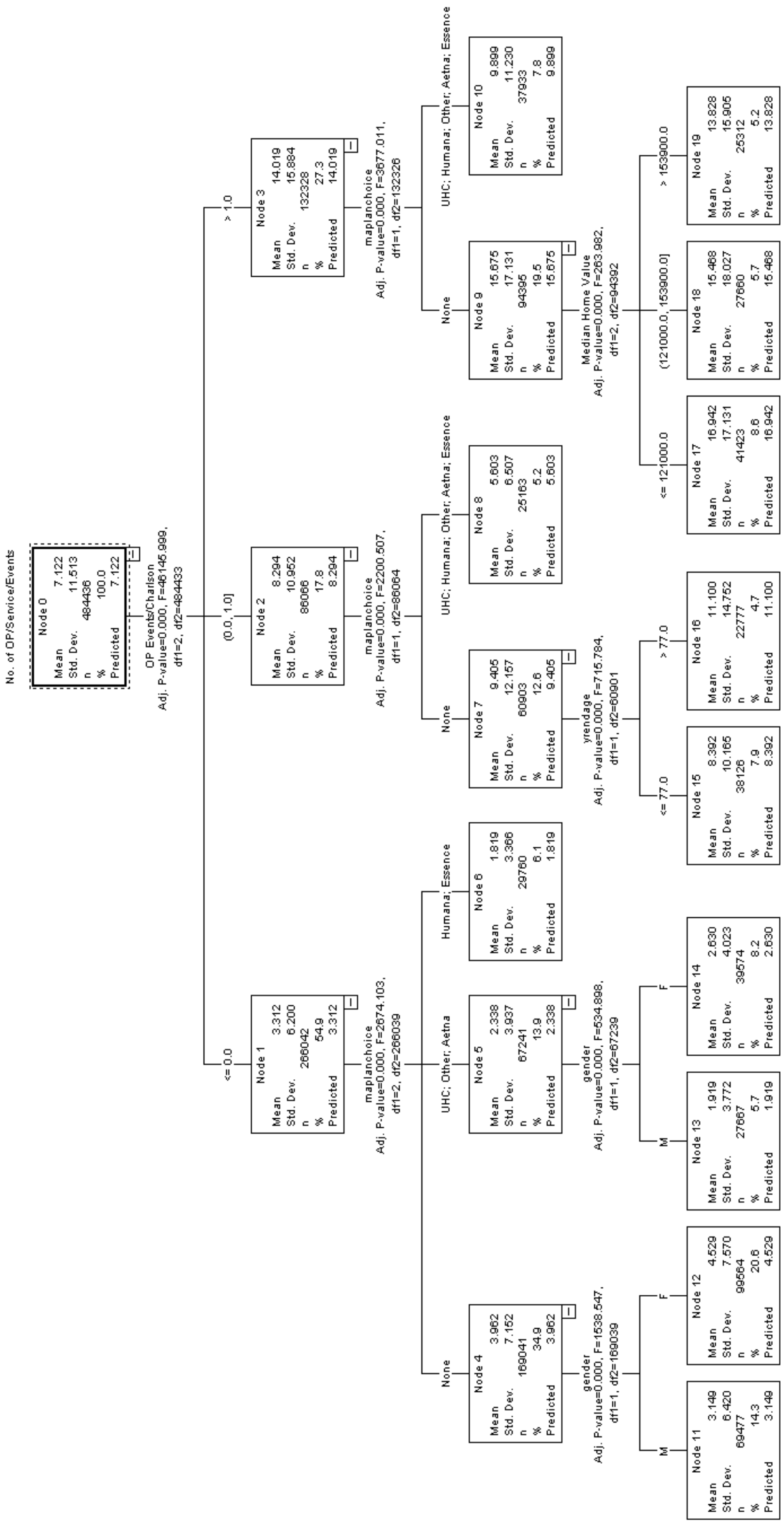
In our first tree (see Exhibit 36), we select the number of inpatient admissions as the target variable. We find that three explanatory variables (inpatient Charlson score, plan choice, and gender) have a strong relationship with inpatient utilization. At level one, the model reveals that the inpatient Charlson score is a strong predictor of inpatient utilization (*p-value* < 0.001, *F value* = 632,697.028, *df1* = 1, *df2* = 484,434). Plan choice emerges at level two, and gender at level three. Predicted inpatient utilization is lowest (27 admissions per 1,000, Node 4) for beneficiaries with Charlson scores = 0 and enrolled in the UHC HMO. Highest utilization (1,653 admissions per 1,000, Node 2) is experienced by beneficiaries with Charlson scores > 0. This is nearly six times greater than the FFS mean. No child nodes appear under Node 4. From this tree, we conclude that a beneficiary's health status, as defined by their inpatient Charlson score, is the primary driver of utilization. For those with a score equal to zero, plan choice is statistically related to FFS beneficiaries experiencing higher utilization than HMO beneficiaries. Also, there is a significant utilization variance between FFS males (41 per 1,000) and FFS females (53 per 1,000). The primary observation is that the group of beneficiaries with Charleson scores > 0 predicts an admission rate <u>38 times greater</u> than those with scores = 0.

Exhibit 36. Multivariate CHAID Tree for Inpatient Services



In our second tree (see Exhibit 37), we examine outpatient activity. The model reveals that three outpatient Charlson score clusters emerging at level one are significant (*p-value* < 0.001, *F value* = 46,145.999, *df1* = 1, *df2* = 484,433). The first cluster (Node 1) represents beneficiaries with outpatient Charlson scores = 0, and they experience the lowest utilization among the three clusters (3,312 outpatient service dates per 1,000). The second cluster (Node 2) represents beneficiaries with outpatient Charlson scores greater than zero and up to a value of 1. Their utilization (8,294 outpatient service dates per 1,000) is greater than those in Node 1. The third cluster (Node 3) represents beneficiaries with outpatient Charlson scores > 1 and having the highest utilization of the Charlson score clusters (14,019 outpatient service dates per 1,000). At level two, plan choice clusters attach to each Charlson score node. Gender, age, and home values are relevant at level three. The highest outpatient utilization is by FFS beneficiaries with Charlson scores > 1 living in zip codes with home values ≤ $121,000 (16,942 service events per 1,000, Node 17). The lowest outpatient utilization is by beneficiaries with Charlson scores = 0 who enroll in either Essence or Humana HMO (1,819 outpatient service dates per 1,000, Node 6). We draw three conclusions from this tree: a) higher outpatient Charlson scores are associated with greater outpatient service utilization, b) beneficiaries enrolled in the FFS plan, especially those likely to be living in lower-income areas, use more outpatient services than those enrolled in the HMO plans, and c) utilization variances exist among the HMO plans.

Exhibit 37. Multivariate CHAID Tree for Outpatient Services



From these two CHAID trees, we demonstrate that variables have interactive and predictive implications for services utilization. For more detailed analyses, we construct Poisson regression models to account for the effects of several explanatory variables on services utilization.

5.4 Service Utilization: Poisson Regression

For the Poisson regressions, we randomly selected 75% of the included sample population (resulting in n = 484,436) for model fitting, reserving the remaining 25% (n = 161,764) for future testing of our models on an independent sample. For each plan and service category, we extended our analysis from the previous 8 variables to 22 variables (see Exhibit 38) in the regressions. With each regression model, any variable failing our p-value test (marginal *p-value* > 0.01) was removed from the model by the backwards elimination process. The full Poisson regression tables (i.e., before removal of variables) are displayed in Appendix N. The reduced Poisson regression models (i.e., after removal of variables that did not contribute statistically significant information on the margin) are discussed in this section.

Exhibit 38. Poisson Regression Variables

Variable	Description
numipadmits	Inpatient admissions based on discharge dates
numOPsrvcevents	Number of Outpatient service date
numCARdiagevents	Nubmer of Carrier events with recorded diagnoses
numhhasrvcrecs	Number of Home health service events
numsnfdiagevents	Skilled nursing events based on discharge dates with recorded diagnoses
maxchscoreallser	Highest charlson score of all service categories
female	Gender selection from male, female, and other
HMOplan	Enrolled in HMO rather than FFS plan
yrendage	Beneficiary age at year end
Black	Race variable sub-category
Hispanic	Race variable sub-category
Asian	Race variable sub-category
Other non-white	Race variable sub-category representing all races other than Black, Hispanic, and Asian
medianhouseeval	Zip code median house value expressed in $100,000 increments
zpctbachelorsormore	Zip code average percent households with bachelors degree or more
zpctmanprofoccs	Zip code average percent of households with managerial or professional employment
hospitalaccess1	Missouri counties having one or more hospitals
hospitalaccess2	Missouri counties without a hospital but having one < 28 miles from county seat
hospitalaccess3	Counties without a hospital and with the nearest hospital being >27 miles from county seat
physiciansper1000	Average number of physicians per 1,000 beneficiaries in a county

The Poisson regression models are presented in a series of exhibits that indicate the formula for the logarithm of the mean number of events for a patient over an entire year, depending on the values of the explanatory (independent) variables. Coefficients of the linear function for the mean (expected value) of the number of events and the standard deviations of the coefficient estimates are followed by the "incidence impacts" for each independent variable. The "incidence impacts" (exp[beta]) are the factors by which the estimated incidence rate (the mean) will change with one-unit increases in the values of individual independent variables if all the other independent variables are held constant. The Z-values reveal the relative impact (worsening of fit) that would occur if the respective variables alone should be removed from the model. The statistical significance of each parameter is computed as a two-tail test using the Z-value. In the following sections, we identify the type and size of the population studied, display the SAS output tables for each Poisson regression model, identify a few of the most significant variables appearing in each model, and summarize our findings.

5.5 All Plans (n = 484,436)

In Exhibit 39, we present the regression results for *inpatient service utilization* by beneficiaries in all plans. The target variable (dependent variable) is the number of hospital discharges (inpatient admissions) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by whether the beneficiary's plan is categorized as FFS versus HMO, and the beneficiaries' age at year-end. After fixing the values of the other seven variables, each unit increase in the maximum Charlson score would increase the expected number of inpatient admissions by 29%. *Ceteris paribus*, enrollees in HMO plans are expected to have 30% fewer inpatient admissions than enrollees in FFS plans. Each additional year of age results in an approximate 2% increase in the number of inpatient admissions per beneficiary.

Exhibit 39. Effects on Inpatient Services for All Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.3315	0.02988	0.03574	-111.489	.0000
maxchscoreallserv	0.2547	0.000704	1.29012	361.966	.0000
female	0.08247	0.005747	1.08597	14.350	.0000
HMOplan	-0.3556	0.006414	0.70076	-55.439	.0000
yrendage	0.01713	0.000361	1.01728	47.506	.0000
Asian	-0.3143	0.05363	0.73030	-5.861	.0000
Othernonwhite	-0.2119	0.02833	0.80904	-7.481	.0000
medianhouseeval	-0.00140	0.000081	0.99860	-17.220	.0000
hospitalaccess1	0.09886	0.009187	1.10391	10.761	.0000

In Exhibit 40, we present the regression results for *outpatient service utilization* by beneficiaries in all plans. The target variable (dependent variable) is the number of outpatient service dates (outpatient services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by whether the beneficiary's plan is categorized as FFS versus HMO, and the beneficiaries' gender. After fixing the values of the other 13 variables, each unit increase in the maximum Charlson score would increase the expected number of outpatient services by 18%. *Ceteris paribus*, enrollees in HMO plans are expected to have 46% fewer outpatient services than enrollees in FFS plans. Females would utilize 24% more outpatient services than males.

Exhibit 40. Effects of Outpatient Services for All Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.0658	0.006369	2.90314	167.35	.0000
maxchscoreallserv	0.1656	0.000163	1.18009	1014.99	.0000
female	0.2122	0.001118	1.23643	189.75	.0000
HMOplan	-0.6223	0.001349	0.53670	-461.19	.0000
yrendage	0.01062	0.000070	1.01067	152.22	.0000
Black	-0.07017	0.002431	0.93224	-28.86	.0000
Hispanic	-0.09815	0.01376	0.90651	-7.13	.0000
Asian	-0.2765	0.009883	0.75845	-27.97	.0000
Othernonwhite	-0.07731	0.004936	0.92560	-15.66	.0000
medianhouseeval	-0.00340	0.000019	0.99661	-181.15	.0000
zpctbachelorsormore	0.000616	0.000104	1.00062	5.94	.0000
zpctmanprofoccs	0.003188	0.000130	1.00319	24.47	.0000
hospitalaccess1	0.09762	0.002431	1.10254	40.16	.0000
hospitalaccess2	0.03418	0.002946	1.03477	11.60	.0000
physiciansper1000	-0.03800	0.000368	0.96271	-103.23	.0000

In Exhibit 41, we present the regression results for *carrier services utilization* by beneficiaries in all plans. The target variable (dependent variable) is the number of carrier service dates (carrier services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by whether the beneficiary's plan is categorized as FFS versus HMO, and the beneficiaries' age at year-end. After fixing the values of the other 13 variables, each unit increase in the maximum Charlson score would increase the expected number of carrier services by 15%. *Ceteris paribus,* enrollees in HMO plans are expected to have 18% fewer carrier services than enrollees in FFS plans. Females are expected to utilize 14% more carrier services than males.

Exhibit 41. Effects on Carrier Services for All Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.7724	0.004510	5.88517	392.96	.0000
maxchscoreallserv	0.1389	0.000118	1.14904	1176.87	.0000
female	0.1309	0.000764	1.13989	171.44	.0000
HMOplan	-0.1953	0.000826	0.82259	-236.42	.0000
yrendage	0.004503	0.000049	1.00451	91.93	.0000
Black	-0.1639	0.001605	0.84887	-102.11	.0000
Hispanic	-0.1796	0.009725	0.83562	-18.47	.0000
Asian	-0.3502	0.006569	0.70457	-53.31	.0000
Othernonwhite	-0.1006	0.003255	0.90433	-30.89	.0000
medianhouseeval	0.000783	0.000013	1.00078	61.00	.0000
zpctbachelorsormore	0.005163	0.000074	1.00518	69.97	.0000
zpctmanprofoccs	-0.00250	0.000095	0.99751	-26.33	.0000
hospitalaccess1	0.04805	0.001869	1.04922	25.71	.0000
hospitalaccess2	0.03849	0.002233	1.03924	17.23	.0000
physiciansper1000	0.005579	0.000240	1.00559	23.20	.0000

In Exhibit 42, we present the regression results for *home health services utilization* by beneficiaries in all plans. The target variable (dependent variable) is the number of home health service events (home health services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiaries' year-end age and whether the beneficiary's plan is categorized as FFS versus HMO. After fixing the values of 11 other variables, each unit increase in the maximum Charlson score would increase the expected number of home health services by 27%. *Ceteris paribus*, each additional year of age results in a 6% increase in the number of home health services per beneficiary. Enrollees in HMO plans are expected to receive 53% fewer home health services than enrollees in FFS plans.

Exhibit 42. Effects on Home Health Services for All Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-4.8312	0.01442	0.00798	-334.997	.0000
maxchscoreallserv	0.2403	0.000335	1.27165	717.704	.0000
female	0.3136	0.002688	1.36831	116.657	.0000
HMOplan	-0.7460	0.003168	0.47426	-235.507	.0000
yrendage	0.05544	0.000153	1.05701	362.237	.0000
Black	0.2120	0.004731	1.23620	44.816	.0000
Hispanic	-0.1640	0.03281	0.84876	-4.998	.0000
Asian	-0.1337	0.02227	0.87487	-6.003	.0000
zpctbachelorsormore	-0.00192	0.000243	0.99808	-7.892	.0000
zpctmanprofoccs	-0.00147	0.000322	0.99853	-4.578	.0000
hospitalaccess1	0.04261	0.006124	1.04353	6.957	.0000
hospitalaccess2	0.02608	0.007536	1.02643	3.461	.0005
physiciansper1000	0.01943	0.000782	1.01962	24.854	.0000

In Exhibit 43, we present the regression results for *skilled nursing facility utilization* by beneficiaries in all plans. The target variable (dependent variable) is the number of skilled nursing discharges (skilled nursing services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiaries' year-end age and whether the beneficiary's plan is categorized as FFS versus HMO. After fixing the values of 10 other variables, each unit increase in the maximum Charlson score would increase the expected number of skilled nursing services by 30%. *Ceteris paribus*, each additional year of age results in an 8% increase in the number of skilled nursing services per beneficiary. Enrollees in HMO plans are expected to receive 59% fewer skilled nursing services than enrollees in FFS plans.

Exhibit 43. Effects on Skilled Nursing Facility Services for All Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-8.3523	0.04499	0.00024	-185.654	.0000
maxchscoreallserv	0.2600	0.000987	1.29691	263.384	.0000
female	0.4524	0.008289	1.57215	54.581	.0000
HMOplan	-0.8711	0.01023	0.41847	-85.146	.0000
yrendage	0.07638	0.000457	1.07937	167.052	.0000
Asian	-0.3605	0.07920	0.69732	-4.552	.0000
Othernonwhite	-0.3715	0.05048	0.68968	-7.360	.0000
medianhouseeval	-0.00313	0.000132	0.99688	-23.754	.0000
zpctbachelorsormore	-0.00198	0.000735	0.99803	-2.688	.0072
zpctmanprofoccs	-0.00541	0.000942	0.99461	-5.743	.0000
hospitalaccess1	0.1321	0.01732	1.14125	7.630	.0000
hospitalaccess2	0.1046	0.02145	1.11022	4.875	.0000

5.6 Fee for Service Plans (n = 324,339)

In Exhibit 44, we present the regression results for *inpatient utilization* by beneficiaries in the FFS plans. The target variable (dependent variable) is the number of hospital discharges (inpatient admissions) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary's year-end age and whether the projected median household value (in hundred thousand dollars) in the zip code where the beneficiary resides. After fixing the values of 7 other variables, each unit increase in the maximum Charlson score would increase the expected number of inpatient admissions by 29%. *Ceteris paribus*, each additional year of age results in a 2% increase in the number of inpatient admissions per beneficiary. Females would experience about 8% more admissions than males.

Exhibit 44. Effects on Inpatient Services for FFS Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.4299	0.03457	0.03239	-99.205	.0000
maxchscoreallserv	0.2566	0.000833	1.29247	308.081	.0000
female	0.07377	0.006767	1.07656	10.902	.0000
yrendage	0.01754	0.000416	1.01770	42.193	.0000
Asian	-0.2714	0.05981	0.76234	-4.537	.0000
Othernonwhite	-0.2407	0.03321	0.78607	-7.247	.0000
medianhouseeval	-0.00109	0.000096	0.99891	-11.309	.0000
hospitalaccess1	0.1135	0.01111	1.12016	10.213	.0000
physiciansper1000	0.003804	0.001887	1.00381	2.016	.0438

In Exhibit 45, we present the regression results for *outpatient service utilization* by beneficiaries in FFS plans. The target variable (dependent variable) is the number of outpatient service dates (outpatient services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, the beneficiary's year-end age, and female gender. After fixing the values of the other eight variables, each unit increase in the maximum Charlson score would increase the expected number of outpatient services by 18%. *Ceteris paribus*, each additional year of age results in a 1% increase in the number of outpatient services per beneficiary. Females would experience about 25% more outpatient services than males.

Exhibit 45. Effect on Outpatient Services for FFS Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	0.8522	0.006273	2.34483	135.862	.0000
maxchscoreallserv	0.1661	0.000184	1.18073	900.784	.0000
female	0.2206	0.001258	1.24684	175.336	.0000
yrendage	0.01385	0.000076	1.01395	181.160	.0000
Black	-0.09638	0.002874	0.90812	-33.537	.0000
Asian	-0.2733	0.01093	0.76084	-25.013	.0000
Othernonwhite	-0.06476	0.005511	0.93729	-11.751	.0000
medianhouseeval	-0.00279	0.000018	0.99721	-156.182	.0000
hospitalaccess1	0.07950	0.001910	1.08274	41.618	.0000
physiciansper1000	-0.02545	0.000380	0.97487	-67.008	.0000

In Exhibit 46, we present the regression results for *carrier services utilization* by beneficiaries in FFS plans. The target variable (dependent variable) is the number of carrier service dates (carrier services) over the year for an individual beneficiary. For this model, the most significant explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary's year-end age, race, and gender. After fixing the values of the other 12 variables, each unit increase in the maximum Charlson score would increase the expected number of carrier services by 15%. *Ceteris paribus*, each additional year of age results in a 0.5% increase in the number of outpatient services per beneficiary. Blacks would experience about 17% fewer outpatient services than Whites. Females would experience about 15% more carrier services than males. We also note that all other non-White races are predicted to receive fewer carrier services than Whites, as do beneficiaries in counties with no close hospital proximity.

Exhibit 46. Effects on Carrier Services for FFS Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.6672	0.005277	5.29729	315.931	.0000
maxchscoreallserv	0.1413	0.000143	1.15175	989.677	.0000
female	0.1407	0.000916	1.15109	153.566	.0000
yrendage	0.004909	0.000057	1.00492	85.562	.0000
Black	-0.1809	0.002106	0.83454	-85.880	.0000
Hispanic	-0.2064	0.01173	0.81347	-17.598	.0000
Asian	-0.3682	0.007697	0.69195	-47.844	.0000
Othernonwhite	-0.1082	0.003846	0.89749	-28.121	.0000
medianhouseeval	0.001110	0.000015	1.00111	72.891	.0000
zpctbachelorsormore	0.004791	0.000086	1.00480	55.877	.0000
zpctmanprofoccs	-0.00201	0.000110	0.99799	-18.261	.0000
hospitalaccess1	0.04454	0.002148	1.04554	20.735	.0000
hospitalaccess2	0.04095	0.002573	1.04180	15.916	.0000
physiciansper1000	0.01149	0.000288	1.01155	39.908	.0000

In Exhibit 47, we present the regression results for *home health services utilization* by beneficiaries in FFS plans. The target variable (dependent variable) is the number of home health service events (home health services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary's year-end age and gender. After fixing the values of the other ten variables, each unit increase in the maximum Charlson score would increase the expected number of home health services by 28%. *Ceteris paribus*, each additional year of age results in a 6% increase in the number of home health services per beneficiary. Females would experience 37% more services than males.

Exhibit 47. Effects on Home Health Services for FFS Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-4.9053	0.01528	0.00741	-321.078	.0000
maxchscoreallserv	0.2434	0.000377	1.27558	645.413	.0000
female	0.3149	0.003026	1.37011	104.073	.0000
yrendage	0.05461	0.000170	1.05613	322.076	.0000
Black	0.3118	0.005402	1.36586	57.713	.0000
Hispanic	-0.1925	0.03772	0.82492	-5.102	.0000
Asian	-0.05569	0.02336	0.94583	-2.384	.0171
medianhouseeval	0.000931	0.000048	1.00093	19.308	.0000
zpctbachelorsormore	-0.00391	0.000116	0.99610	-33.769	.0000
hospitalaccess1	0.01456	0.006803	1.01467	2.140	.0323
hospitalaccess2	0.01724	0.008263	1.01739	2.086	.0370
physiciansper1000	0.02818	0.000865	1.02858	32.577	.0000

In Exhibit 48, we present the regression results for *skilled nursing facility utilization* by beneficiaries in FFS plans. The target variable (dependent variable) is the number of skilled nursing discharges (skilled nursing services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiaries' year-end age and female gender. After fixing the values of 10 other variables, each unit increase in the maximum Charlson score would increase the expected number of skilled nursing services by 30%. *Ceteris paribus*, each additional year of age results in an 8% increase in the number of skilled nursing services per beneficiary. Females are expected to receive 58% more skilled nursing services than males.

Exhibit 48. Effects on Skilled Nursing Services for FFS Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-8.3992	0.04901	0.00023	-171.371	.0000
maxchscoreallserv	0.2600	0.001099	1.29699	236.590	.0000
female	0.4600	0.009187	1.58408	50.069	.0000
yrendage	0.07732	0.000498	1.08039	155.113	.0000
Black	0.04573	0.01726	1.04679	2.650	.0081
Asian	-0.3039	0.08380	0.73790	-3.627	.0003
Othernonwhite	-0.4449	0.05789	0.64090	-7.685	.0000
medianhouseeval	-0.00291	0.000146	0.99709	-19.965	.0000
zpctbachelorsormore	-0.00280	0.000801	0.99720	-3.496	.0005
zpctmanprofoccs	-0.00685	0.001024	0.99317	-6.693	.0000
hospitalaccess1	0.1354	0.01847	1.14499	7.332	.0000
hospitalaccess2	0.1214	0.02279	1.12908	5.328	.0000

5.7 HMO Plans (n = 160,097)

In Exhibit 49, we present the regression results for *inpatient utilization* by beneficiaries in the HMO plans. The target variable (dependent variable) is the number of hospital discharges (inpatient admissions) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary’s year-end age and gender. After fixing the values of seven other variables, each unit increase in the maximum Charlson score would increase the expected number of inpatient admissions by 29%. *Ceteris paribus*, each additional year of age results in about a 2% increase in the number of inpatient admissions per beneficiary. Females would experience about 12% more admissions than males.

Exhibit 49. Effects on Inpatient Services for HMO Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.3919	0.05991	0.03364	-56.620	.0000
maxchscoreallserv	0.2511	0.001319	1.28543	190.383	.0000
female	0.1103	0.01092	1.11665	10.100	.0000
yrendage	0.01638	0.000728	1.01651	22.512	.0000
Black	-0.06934	0.01837	0.93301	-3.774	.0002
Asian	-0.4972	0.1215	0.60823	-4.093	.0000
medianhouseeval	-0.00249	0.000165	0.99751	-15.143	.0000
hospitalaccess1	0.06064	0.01998	1.06252	3.035	.0024
physiciansper1000	-0.01386	0.003103	0.98623	-4.468	.0000

In Exhibit 50, we present the regression results for *outpatient service utilization* by beneficiaries in HMO plans. The target variable (dependent variable) is the number of outpatient service dates (outpatient services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by median home value and female gender. After fixing the values of the other eight variables, each unit increase in the maximum Charlson score would increase the expected number of outpatient services by about 18%. *Ceteris paribus*, females would experience about 18% more outpatient services than males. Each $100,000 increase in median home value predicts about a 27% reduction in the number of outpatient services per beneficiary.

Exhibit 50. Effects on Outpatient Services for HMO Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.6530	0.01337	5.22265	123.606	.0000
maxchscoreallserv	0.1626	0.000343	1.17651	474.463	.0000
female	0.1687	0.002407	1.18376	70.078	.0000
yrendage	-0.00283	0.000166	0.99717	-17.027	.0000
Black	-0.1017	0.004282	0.90329	-23.754	.0000
Asian	-0.2854	0.02272	0.75168	-12.566	.0000
Othernonwhite	-0.08304	0.01089	0.92031	-7.624	.0000
medianhouseeval	-0.00315	0.000036	0.99685	-88.433	.0000
hospitalaccess1	0.06425	0.004145	1.06636	15.501	.0000
physiciansper1000	-0.04457	0.000712	0.95641	-62.607	.0000

In Exhibit 51, we present the regression results for *carrier services utilization* by beneficiaries in HMO plans. The target variable (dependent variable) is the number of carrier service dates (carrier services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the female gender and Black race. After fixing the values of the other 12 variables, each unit increase in the maximum Charlson score would increase the expected number of carrier services by about 14%. *Ceteris paribus*, females would experience about 12% more carrier services than males, and Blacks would utilize about 12% fewer carrier services than other races.

Exhibit 51. Effects on Carrier Services for HMO Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.8691	0.008719	6.48259	214.374	.0000
maxchscoreallserv	0.1343	0.000210	1.14374	640.337	.0000
female	0.1089	0.001383	1.11503	78.702	.0000
yrendage	0.003678	0.000094	1.00368	38.994	.0000
Black	-0.1253	0.002504	0.88226	-50.034	.0000
Hispanic	-0.1179	0.01739	0.88877	-6.781	.0000
Asian	-0.3146	0.01260	0.73008	-24.960	.0000
Othernonwhite	-0.08011	0.006111	0.92301	-13.108	.0000
medianhouseeval	-0.00025	0.000024	0.99975	-10.366	.0000
zpctbachelorsormore	0.006127	0.000145	1.00615	42.318	.0000
zpctmanprofoccs	-0.00392	0.000186	0.99609	-21.050	.0000
hospitalaccess1	0.06422	0.003798	1.06633	16.908	.0000
hospitalaccess2	0.04059	0.004507	1.04143	9.008	.0000
physiciansper1000	-0.01096	0.000441	0.98910	-24.847	.0000

In Exhibit 52, we present the regression results for *home health services utilization* by beneficiaries in HMO plans. The target variable (dependent variable) is the number of home health service events (home health services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary's year-end age, and female gender. After fixing the values of the other 11 variables, each unit increase in the maximum Charlson score would increase the expected number of home health services by about 26%. *Ceteris paribus*, each additional year of age results in an approximate 6% increase in the number of outpatient services per beneficiary. Females would experience about 37% more services than males.

Exhibit 52. Effects on Home Health Services for HMO

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-5.1853	0.03474	0.00560	-149.255	.0000
maxchscoreallserv	0.2298	0.000731	1.25835	314.583	.0000
female	0.3171	0.005861	1.37310	54.099	.0000
yrendage	0.06043	0.000357	1.06229	169.088	.0000
Black	-0.03439	0.009951	0.96619	-3.456	.0005
Asian	-0.7271	0.07401	0.48331	-9.824	.0000
Othernonwhite	-0.1475	0.03161	0.86289	-4.665	.0000
medianhouseeval	-0.00467	0.000099	0.99534	-47.290	.0000
zpctbachelorsormore	0.009152	0.000607	1.00919	15.069	.0000
zpctmanprofoccs	-0.01246	0.000772	0.98762	-16.144	.0000
hospitalaccess1	0.2286	0.01553	1.25683	14.715	.0000
hospitalaccess2	0.1287	0.01867	1.13736	6.894	.0000
physiciansper1000	-0.02838	0.001758	0.97202	-16.142	.0000

In Exhibit 53, we present the regression results for *skilled nursing facility utilization* by beneficiaries in FFS plans. The target variable (dependent variable) is the number of skilled nursing discharges (skilled nursing services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiaries' year-end age and gender. After fixing the values of 7 other variables, each unit increase in the maximum Charlson score would increase the expected number of skilled nursing services by about 30%. *Ceteris paribus*, each additional year of age results in an approximate 7% increase in the number of skilled nursing services per beneficiary. Females are expected to receive about 52% more skilled nursing services than males.

Exhibit 53. Effects on Skilled Nursing Services for HMO Plans

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-9.0056	0.09973	0.00012	-90.298	.0000
maxchscoreallserv	0.2609	0.002259	1.29803	115.487	.0000
female	0.4218	0.01930	1.52475	21.857	.0000
yrendage	0.07129	0.001153	1.07389	61.826	.0000
Black	-0.2170	0.03288	0.80490	-6.601	.0000
Asian	-0.7058	0.2428	0.49370	-2.907	.0036
medianhouseeval	-0.00328	0.000280	0.99673	-11.711	.0000
hospitalaccess1	0.2116	0.03593	1.23569	5.891	.0000
physiciansper1000	-0.02215	0.005246	0.97809	-4.223	.0000

5.8 Essence HMO (n = 24,114)

In this section, we examine the results specifically for Essence HMO, the plan with known RB-PCPs, so that comparisons are made to the previously presented plan segments. In Exhibit 54, we present the regression results for *inpatient utilization* by beneficiaries in the Essence HMO plan. The target variable (dependent variable) is the number of hospital discharges (inpatient admissions) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary’s year-end age and female gender. After fixing the values of 10 other variables, each unit increase in the maximum Charlson score would increase the expected number of inpatient admissions by 26%. *Ceteris paribus*, each additional year of age results in an approximate 1% increase in the number of inpatient admissions per beneficiary. Females would experience about 12% more inpatient admissions than males.

Exhibit 54. Effects on Inpatient Services for Essence HMO

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.7624	0.1597	0.02323	-23.5633	.0000
maxchscoreallserv	0.2337	0.004024	1.26323	58.0696	.0000
female	0.1120	0.03121	1.11856	3.5897	.0003
yrendage	0.01349	0.002080	1.01359	6.4887	.0000

In Exhibit 55, we present the regression results for *outpatient service utilization* by beneficiaries in HMO plans. The target variable (dependent variable) is the number of outpatient service dates (outpatient services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson score computed from diagnostics recorded in delivery of any medical service over the year, followed by median home value and female gender. After fixing the values of the other eight variables, each unit increase in the maximum Charlson score would increase the expected number of outpatient services by about 17%. *Ceteris paribus*, each $100,000 increase in median home value predicts an approximate 46% reduction in the number of outpatient services per beneficiary. Females would experience about 26% more outpatient services than males.

Exhibit 55. Effects on Outpatient Services for Essence HMO

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	2.3260	0.05068	10.2373	45.899	.0000
maxchscoreallserv	0.1533	0.001048	1.1657	146.255	.0000
female	0.2316	0.007075	1.2606	32.739	.0000
yrendage	-0.00993	0.000497	0.9901	-19.969	.0000
Black	-0.09666	0.01113	0.9079	-8.681	.0000
medianhouseeval	-0.00615	0.000162	0.9939	-37.940	.0000
zpctbachelorsormore	0.008488	0.000929	1.0085	9.135	.0000
zpctmanprofoccs	-0.00343	0.001211	0.9966	-2.835	.0046
hospitalaccess2	0.4150	0.01578	1.5143	26.298	.0000
physiciansper1000	-0.04566	0.002093	0.9554	-21.812	.0000

In Exhibit 56, we present the regression results for *carrier services utilization* by beneficiaries in Essence HMO. The target variable (dependent variable) is the number of carrier service dates (carrier services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the Black race and female gender. After fixing the values of the other 12 variables, each unit increase in the maximum Charlson score would increase the expected number of carrier services by about 13%. *Ceteris paribus*, blacks would utilize approximately 15% fewer carrier services than other races, and females would experience about 11% more carrier services than males.

Exhibit 56. Effects on Carrier Services for Essence HMO

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.8692	0.02214	6.48282	84.440	.0000
maxchscoreallserv	0.1246	0.000572	1.13272	217.870	.0000
female	0.1007	0.003653	1.10593	27.565	.0000
yrendage	0.002672	0.000252	1.00268	10.599	.0000
Black	-0.1588	0.005752	0.85314	-27.614	.0000
Othernonwhite	-0.07440	0.01580	0.92830	-4.710	.0000
medianhouseeval	-0.00033	0.000079	0.99967	-4.153	.0000
zpctmanprofoccs	0.002945	0.000182	1.00295	16.153	.0000
physiciansper1000	-0.00998	0.000980	0.99007	-10.186	.0000

In Exhibit 57, we present the regression results for *home health services utilization* by beneficiaries in HMO plans. The target variable (dependent variable) is the number of home health service events (home health services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiary's year-end age and female gender. After fixing the values of the other eight variables, each unit increase in the maximum Charlson score would increase the expected number of home health services by about 21%. *Ceteris paribus*, each additional year of age results in an approximate 5% increase in the number of outpatient services per beneficiary. Each $100,000 increase in median home value predicts about a 74% decrease in home health services per beneficiary. Why is this? Perhaps those with greater wealth have other alternatives such as the employment of an in-home caregiver or the ability to afford more frequent visits with physicians or other providers. This is another area for further exploration.

Exhibit 57. Effects on Home Health Services for Essence HMO

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-2.8731	0.1435	0.05652	-20.0185	.0000
maxchscoreallserv	0.1895	0.003085	1.20865	61.4336	.0000
female	0.3331	0.02246	1.39529	14.8335	.0000
yrendage	0.04457	0.001402	1.04558	31.7897	.0000
Black	-0.5321	0.04072	0.58737	-13.0677	.0000
Othernonwhite	-0.2319	0.1141	0.79306	-2.0324	.0421
medianhouseeval	-0.01331	0.000467	0.98678	-28.4864	.0000
zpctbachelorsormore	0.008752	0.002925	1.00879	2.9921	.0028
zpctmanprofoccs	-0.00867	0.003809	0.99137	-2.2762	.0228
physiciansper1000	-0.07373	0.005906	0.92892	-12.4839	.0000

In Exhibit 58, we present the regression results for skilled nursing facility utilization by beneficiaries in FFS plans. The target variable (dependent variable) is the number of skilled nursing discharges (skilled nursing services) over the year for an individual beneficiary. For this model, the greatest explanatory power (on the margin) is provided by the maximum Charlson co-morbidity score computed from diagnostics recorded in delivery of any medical service over the year, followed by the beneficiaries' year-end age and gender. After fixing the values of 3 other variables, each unit increase in the maximum Charlson score would increase the expected number of skilled nursing services by about 29%. Ceteris paribus, each additional year of age results in an approximate 7% increase in the number of skilled nursing services per beneficiary. Females are expected to receive about 50% more skilled nursing services than males.

Exhibit 58. Effects on Skilled Nursing Services for Essence HMO

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-9.9249	0.3191	0.00005	-31.1042	.0000
maxchscoreallserv	0.2566	0.008153	1.29254	31.4757	.0000
female	0.4087	0.06678	1.50489	6.1204	.0000
yrendage	0.07036	0.003942	1.07289	17.8472	.0000
Black	-0.4007	0.09691	0.66986	-4.1348	.0000

5.9 Poisson Regressions Summary

In Table 18, we display the three variables showing the most significant impact for each service for each plan. The Charlson score consistently presents as one of the top three factors of most significant impact in every service for every plan. We also note that the selection of an HMO plan predicts a substantial decline in service utilization of all types. Compared to males, females are predicted to use more services of all types. Blacks are predicted to use fewer carrier services than other races. Interestingly, increases in median home value are associated with decreased outpatient service usage for beneficiaries in HMO plans. Age sometimes has an effect, most notably for home health and skilled nursing services.

For Essence, the “Median Home Value” variable is prominent in both outpatient and home health services and that variable has a sizable, negative impact on utilization for those services. Perhaps Essence has an operational strategy to constrain those services. Perhaps there are less costly alternatives available from its schedule of benefits. Perhaps aggressive care management by RB PCPs results in demand reduction for those services. Perhaps the beneficiaries in the other plan categories are experiencing over-utilization for some reason. Whatever the cause, this is a curiosity for further exploration.

From the Poisson regressions, we conclude that beneficiary traits and plan selection have a statistically significant effect on service utilization. These results support our H2.

Table 18 Summary of Poisson Regressions: Effects of Top 3 Variables for Each Service

Summary of Poisson Regressions: Effects of Top 3 Variables for Each Service

Service	Variable	All Plans	FFS	HMO	Essence
Inpatient	Charlson Score	29%	29%	29%	26%
	HMO Plan	-30%			
	Female		8%	12%	12%
	Age	2%	2%	2%	1%
Outpatient	Charlson Score	18%	18%	18%	17%
	HMO Plan	-46%			
	Female	24%	25%	18%	26%
	Age		1%		
	Median Home Value			-27%	-46%
Carrier	Charlson Score	15%	15%	14%	13%
	HMO Plan	-18%			
	Female	14%	15%	12%	11%
	Black		-17%	-12%	-15%
Home Health	Charlsons Score	27%	28%	26%	21%
	HMO Plan	-53%			
	Female		37%	37%	40%
	Age	6%	6%	6%	
	Median Home Value				-74%
Skilled Nursing	Charlson Score	30%	30%	30%	29%
	Plan Choice	-59%			
	Female		58%	52%	50%
	Age	8%	8%	7%	7%

5.10 Services Mix

One additional analysis drawn from this research is an examination of the mix of services by plan. In Table 19, for each service category, we show the service counts as percentages of total services for FFS, all HMOs, and Essence plans. The table reveals significant differences in the services mix experienced by beneficiaries in each plan category, and an interesting pattern emerges. Compared to the FFS beneficiaries, the HMO beneficiaries have a lesser proportion of services attributable to inpatient, outpatient, home health, and skilled nursing services and a greater proportion attributable to carrier services. These differences are even more pronounced when comparing FFS and Essence results.

Carrier services include entities such as physician medical practices and non-hospital-based services such as ambulatory surgery centers, free-standing imaging centers, and retail laboratories. We learned from our field research that these carrier services generally represent less costly alternatives to hospital-based services (both inpatient and outpatient) and, therefore, MAOs and risk-bearing PCP groups prefer them. This suggests that the use of more carrier services results in a reduction of all other services. Further research is needed to demonstrate the legitimacy of this claim and to determine if there are cost implications. Nevertheless, we can conclude that the mix of services is predicted to differ between FFS and HMO plans. The Essence results also suggest that the presence of RB PCPs also may materially impact services utilization.

Table 19

Service Mix by Plan Type (Using Counts per 1,000 Beneficiaries)

Service Categories	FFS		ALL HMOs		Essence Only	
	Count	% of Total Count	Count	% of Total Count	Count	% of Total Count
Inpatient Discharges	279	0.49%	217	0.45%	172	0.38%
Outpatient Service Dates	8,364	14.76%	4,551	9.40%	3,454	7.60%
Carrier Service Dates	46,435	81.95%	42,781	88.38%	41,443	91.18%
Home Health Service Dates	1,512	2.67%	803	1.66%	343	0.75%
Skilled Nursing Discharges	73	0.13%	52	0.11%	38	0.08%
Total Services per 1000 Beneficiaries	56,663	100.00%	48,404	100.00%	45,450	100.00%

5.11 Hypotheses Summary

Hypothesis 1. Using CHAID decision trees, we tested eight predictor (explanatory) variables against the target variable of the Medicare plan choice. The results demonstrate that Medicare plan choice is statistically related to specific beneficiary characteristics (age, gender, race, health status), the medical services available in the beneficiary's county of residence (i.e., physician count, hospital proximity), and the demographic characteristics of individuals who reside in the same Postal Zip code (education level and median household income). As a group, seven of the eight predictor variables showed statistical relationships to Medicare plan choice. Hypothesis 1 is supported.

Hypothesis 2. Again, using CHAID decision trees, we examined the relationships of nine variables (age, gender, race, health status, physician count, hospital proximity, education level, household income, and plan choice) to each of the five service categories. The results show that the medical services received by Medicare beneficiaries vary according to beneficiary characteristics (age, gender, race, health status), insurance plan choice (Traditional Medicare, Medicare Advantage), medical services available in the beneficiary's county of residence (physician count, hospital proximity), and the demographic characteristics of individuals who reside in the same Postal Zip code (education level and median household income). We also produced a series of Poisson regression models to investigate the impact of 22 variables on each of the service categories in each plan. Again, we demonstrated that variables such as health status (i.e., Charlson score), gender, race, median home value, and the choice of an HMO plan impact service utilization. Collectively, these findings support H2.

Hypothesis 3. We note that our study does not explicitly include an analysis of service utilization by beneficiaries receiving care from specifically identified RB PCPs. However, our field research confirms that Essence HMOs engage RB PCPs to serve as medical gatekeepers, and each Essence beneficiary is assigned to one of the RB PCP. Accordingly, we offer the Essence plan as a proxy for a network of RB PCPs. We conducted tests of differences in means of the five service categories for each of six plan types (Traditional Medicare, All Medicare Advantage Plans, Essence, UHC, Humana, and Aetna). The results show that the mean utilization statistic for each service category, except carrier services, is lowest for Essence beneficiaries. We also examined the mix of services and found that Essence beneficiaries experience a mix that differs from both FFS and other HMO beneficiaries, including proportionately lesser use of inpatient, skilled nursing, outpatient, and home health services. These finding support our hypothesis that beneficiaries of medical groups with risk-sharing reimbursement schemes will have lower utilization of medical services than do patients of physicians who practice under FFS arrangements. However, because this research was not conducted at the physician level (rather than through the use of a proxy such as Essence), we can only state that support of H3 is suggested and that further examination is required.

Chapter 6: Discussion

We developed a comprehensive method for analyzing healthcare services utilization using data from several hundred thousand Missouri beneficiaries. Furthermore, the method is valid for studying medical services usage by any patient population for which detailed records of medical treatments and diagnoses are available.

We demonstrate that beneficiary traits and access to providers are associated with Medicare plan choice, and all of those (traits, access, and plan choice) are statistically related to utilization of services. Also, we provide some evidence that the presence of RB PCPs in HMO plans results in less utilization of non-carrier services as compared to other plans, especially the FFS plan.

We lay the groundwork for further investigation of factors affecting mix of services received by patients and services rendered by medical practices under different insurance coverages for patients and reimbursement practices for practitioners. In the following sections, we present the implications of our research, opportunities for future research, and concluding comments.

6.1 Implications

Operationally and clinically, the U.S. healthcare industry is complex, and the associated data are massive. The industry needs skilled, knowledgeable researchers to address industry challenges. For example, a significant component of the Medicare program, specifically Medicare Part A (inpatient care benefits), is headed toward a solvency problem (kff.org, 2019) in the year 2026. This is the estimated timeframe when the Part A Trust Fund will encounter two problems: a) incoming revenues will be less than benefits spending, and b) the fund's assets will be depleted. Without sufficient changes, Medicare will not be able to pay for all of the costs of the current Part A benefits commitment.

Solutions are needed to contain or reduce services utilization and associated costs. Researchers and practitioners have the opportunity to offer solutions to policymakers. By documenting the strengths and weaknesses of current plan offerings, researchers might uncover more and better opportunities that lead to improved plan design at lower costs for better care. Furthermore, with data already available from CMS, advanced data analytics can be used for health policy and insurance plan refinements that better serve the healthcare needs of specific beneficiaries based on their attributes, access to care, plan choice tendencies, and provider compensation arrangements

Stakeholders want strategies to contain Medicare costs. By understanding the role of each stakeholder as described in our Cascading Agency Theory model, one might better understand how to generate cost containment strategies for both the Medicare and Medicare Advantage enterprises. As one strategy, CMS has been transitioning Traditional Medicare enrollment to Medicare Advantage enrollment. This transition is done, in part, by encouraging private entities to become MAOs and to accept the administrative responsibilities, financial risks, and financial rewards associated with member recruitment into their Medicare Advantage plans, thereby increasing beneficiary access to the Medicare Advantage alternative. Approximately one-third of Medicare beneficiaries are now Medicare Advantage enrollees, and Medicare Advantage enrollment has been growing at an annual rate of about 7% (kff.org, 2019). Supplementing existing research with additional information that reveals the effects of beneficiary traits on plan choice offers a greater understanding of why beneficiaries increasingly select the Medicare

Advantage alternative. When they do, those traits and plan choices will help predict services utilization, thereby offering an improved capability for predicting costs. Using statistical models of the type demonstrated in this dissertation, stakeholders in healthcare delivery can compare services received or delivered against norms that adjust for patient characteristics and practice setting.

Our research also suggests that successful MAOs might benefit from engaging RB entities with experienced PCPs who will render clinically sound and financially prudent medical care and care management services to the Medicare Advantage beneficiaries assigned to them. We learned from our discussions with Harmony PCPs and their MAOs, that cooperation and shared data enable both groups to succeed financially. Also important for this success is peer-to-peer discussion, education, and review among the PCPs. We also learn from their joint operating reports that over 90% of the beneficiaries extend their enrollment in the same plan year after year. By understanding the problems predicted by agency theory, such as information asymmetry, the moral hazard of agent self-interest, and agent's risk-aversion, the MAOs have an opportunity to mitigate those problems through the development of mutually beneficial contracts with RB entities that wish to engage as willing partners.

In Appendix A of our study, we offer several conceptual examples of RB contract components that have been in place for several years. Given the longevity of these types of contract terms, we conclude that the MAOs and RB PCPs find these types of terms to be agreeable. Our research also suggests that patients of RB PCPs receiving adequate financial incentives (and timely information) will utilize fewer services than their FFS counterparts, thus delighting their MAOs. This outcome reinforces the MAOs' decisions to enter into and sustain their CMS contracts and grow their memberships, thereby helping CMS achieve its stated strategy of shifting beneficiaries from Traditional Medicare to Medicare Advantage.

6.2 Limitations

6.2.1 Data. Our study is subject to some important limitations. The study is conducted from Missouri-only data, so the results may not be generalizable to the entire Medicare beneficiary population. However, in many categories such as population, geographical size, and household income, Missouri ranks near the average of all states and, therefore, one might expect Missouri to be representative of a significant portion of the Medicare population. Each state, however, has its own regulatory regimes for medical insurance and medical practices and varies in concentration of medical facilities and practicing professionals. Further, each state has differing histories with Medicare Advantage plans; thus, patient care utilization management may be more advanced in some regions.

The Traditional Medicare (FFS) claims data used in this research are dependent upon claims filings. Claims are processed by third parties known as Medicare Administrative Contractors (MAC). Among other duties, the MACs are responsible for the processing and payment of claims from providers and reporting a vast amount of data to CMS. Consequently, the accuracy, thoroughness, and timeliness of claims data may be subject to errors and omissions by providers, MACs, and CMS. To mitigate these concerns, CMS and its contractors undertake a regular and rigorous review of claims data (https://www.cms.gov/Research-Statistics-Data-and-Systems/Monitoring-

Programs/Medicare-FFS-Compliance-Programs/Recovery-Audit-Program; MedPAC, 2020).

Similarly, the Medicare Advantage (HMO) encounter data used in this research are dependent upon MAOs' efforts to collect and report data that are accurate, thorough, and timely. According to MedPAC, in recent years, data collection efforts have improved with the advent of more performance-driven payments to providers. MedPAC states that researchers must be cautious in their use of these data as the data continue to evolve in accuracy. In its March 2020 report to Congress, MedPAC reported that the data were improved from prior years, but that further work is required to assure greater data accuracy. Because of need for complete and accurate data, and with MedPAC's recommendation, CMS continues its efforts to improve data reporting by plans and providers by establishing better audits and higher standards for reporting (MedPAC, 2020).

6.2.2 Gauging health status. Another limitation is our selection of the Charlson Co-morbidity Index scoring tool to measure health status. This tool is only one of several available. Researchers may prefer to adopt or modify the CCMI algorithm used in this study or utilize other methods such as the Elixhauser Index, Chronic Disease Score, or Health-related Quality of Life Comorbidity Index. The predictive validity of these various methods is dependent upon the characteristics of the patients being observed, the purpose of the study, and the sources of data used to construct the indicator (Ou, Mukherjee, Erickson, Piette, Bagozzi, & Balkrishnan, 2012). CMS continues to refine its metrics to determine a beneficiary's health status, in part, to determine capitation amounts to pay to MAOs. Nevertheless, the beneficiaries' "official" risk scores are available to researchers only for the calendar year 2014. At this time, we do not know when risk scores for other years will be released. Hence, we do not know if our calculations will materially yield the same results produced by CMS for the not-yet-published 2016 scores. With diagnostic data in the individual encounter records, however, it is possible to produce alternative indicators of patients' health status which may be more sensitive than co-morbidity indicators for predicting needs for specific medical services.

6.2.3 Beneficiary traits. The Medicare files do not contain any variables for "level of education" or "household wealth." Our surrogate variables are obtained from U.S. Census-related data as organized by zip code tabulation areas (ZCAT), based on results from the American Household Survey. In this study, for these two attributes, we use averages based on individuals residing within the same ZCAT.

6.2.4 Quality considerations. This study does not address the quality of care rendered by clinicians or the clinical outcomes experienced by beneficiaries. It is our experience that conversations involving healthcare *quantity* inevitably lead to corollary discussions regarding healthcare *quality*. Some may contend that quantity reduction can lead to quality reduction. Search engines produce thousands of articles, editorials, research papers, public policy statements, and other published subject matter on the topic, and the topic is broad. We find that attempts to define healthcare quality can be very narrow, such as for specific surgical procedures (Yuan & Chung, 2016), or more comprehensive, such as for an industry-wide standard (AHRQ, 2020). Busse, Panteli, and Quinten (2019) write: "despite the vast literature base and its universal acknowledgment of its importance in health systems, there is no common understanding of the term 'quality of care,' and there is disagreement about what it encompasses." In proposing a framework for defining quality, one research team acknowledges "the fact that patients, clinicians, leaders, and other stakeholders might have different perspectives on health-care quality makes it even harder to standardize and harmonize different conceptual models of quality" (Nylenna, Bjertnaes, Saunes, and Lindahl, 2015). Others propose that the absence of a standard characterization of healthcare quality, and the tensions created, may be valuable. For example, Mitchell, Cribb, & Entwistle (2019) argue that efforts to generalize or coordinate industry-wide definitions of quality could squash local and legitimate quality initiatives, thereby limiting pathways to further quality improvements. Consequently, in this study, we do not attempt to define or report quality and leave that to future research. With an additional year of data, however, it would be possible to use the detailed diagnostic information to examine how health status in the succeeding year is affected by health status and services received in the previous year. This presents an opportunity to introduce some type of quality component into the study.

Our agency structure is but one set of forces that might influence the quantity and quality of care received by patients. In discussions with medical practitioners, the author has found that physicians inherently seek to provide high quality care and are motivated by factors such as:

- The "Calling" to be a doctor;
- The Hippocratic oath;
- Personal and professional pride;
- Preserving one's community reputation;
- Achieving patient and family satisfaction with services rendered;

- Peer review by professional colleagues of one's clinical activity;
- Peer review by MAOs of one's clinical and patient satisfaction outcomes;
- Rewards and penalties based on patient satisfaction and clinical outcome metrics;
- The threat of malpractice lawsuits;
- State sanctions, including loss of professional license; and
- The threat of federal penalties due to improper medical care.

It may be possible to develop indicators of some of these forces and consider them additionally when comparing services rendered in different environments. In this study, however, there is no intention to measure quality as it relates to services utilization, appropriateness or outcomes. For some, that may represent an important limitation. Accordingly, we leave open the discussion of quality for future research.

6.2.5 Additional Comments. Despite the need for further investigation of the accuracy and uniformity of data furnished to CMS by MAOs , the quantitative methods presented herein collectively lay a foundation for productive multi-year studies of CMS data as further evolution occurs in medical insurance programs for individuals and reimbursement arrangements for service delivery.

6.3 Future Research

At this time, the Medicare Advantage encounter data were available only for calendar years 2015 (released by CMS in 2018) and 2016 (released in 2019). (Data for 2017 were subsequently released in 2020). This study uses the data for the most recent year available (2016), a year for which master beneficiary information also was comparatively complete for enrollees in HMO plans. In 2015, the healthcare industry underwent a significant transition from ICD-9 to ICD-10 diagnosis coding, and we are aware of concerns about coding accuracy in that year. This reinforces our decision to use only 2016 data.

Should researchers be granted permission to review contract terms between MAOs and providers (perhaps CMS should mandate such disclosure), their analyses could expand to include the effects those terms have on many elements such as beneficiary plan choice, enrollment trends, and services utilization. It is possible, perhaps likely, that specific contract terms drive long-term principal-agent relationships, accelerate enrollment of MAO beneficiaries, and contribute to optimal service utilization patterns.

The granularity of the Traditional Medicare and Medicare Advantage datasets offers a treasure trove of research opportunities, and we envision several additional opportunities for ongoing research. Healthcare utilization can be analyzed by procedure, diagnosis, patient, provider, plan, MAO, and demographical traits. Accordingly, we suggest several future research topics to advance the Medicare body of knowledge.

Refinement of the Poisson regression models. When the Poisson regression models were applied to individual cases and the cases were sorted according to the estimated number of encounters for each type of service, it was apparent that predictions could be refined to accommodate nonlinear impacts of Charlson scores and age of patient on the log (expected encounters). Such refinements did not affect the statistical significance of the factors included in the models presented in this dissertation or materially affect the total number of services of a particular type that were predicted to be delivered under the different insurance plans. They did, however, result in more accurate estimates for population subgroups. Results of experiments with alternative methods of incorporating these effects will be reported in future work.

Other regions. Results using this (or similar) methodology with data from other locales, states, and regions will help determine if the results from this study are generalizable to the entire Medicare population.

Plan choice. In our research, we presented evidence that a beneficiary's demographical characteristics and access to care may affect their Medicare plan choice and service utilization. Policymakers and MAOs alike may be interested in further investigation into this line of research for tactical development of plans and benefits schedules best suited for the beneficiaries they seek to accommodate. For example, would CMS' cost to incentivize MAOs and their healthcare providers to increase their presence in an underserved community be less than the long-term cost attributable to a presumably less healthy population? Or, could plan benefit structures somehow better incentivize beneficiaries in underserved areas to be more proactive in seeking preventative care in neighboring counties? These types of analyses are compelling opportunities to expand research in these areas.

Effect of service prices on referrals. The Traditional Medicare (FFS) data contain payment information for each healthcare service received, including the service location and rendering provider. For each service event, there is a record of the specific amounts paid by the Medicare program, secondary and supplemental insurers, and beneficiaries. The sum of those payments is the total cost of the service. Researchers could determine if the total cost of a specific service (or service provider) has a relationship to the RB PCPs' patient referral patterns. If so, this suggests that RB PCPs are price sensitive and may actively seek out low-cost providers as one strategy to minimize expense payments from their medical risk pools.

PCP practice-based services. Researchers could examine the medical practice-based procedure codes and volumes reported by both RB PCPs and FFS PCPs to determine if one cohort offers a broader selection of services as compared to the other. The RB PCPs whom we interviewed believe they offer a comprehensive array of medical practice-based services as another strategy to minimize both their referrals and the associated deductions from their medical risk pools. We are not aware of any research that supports their viewpoint, but the Medicare claims data are available to conduct such research.

Medical practice modeling. Medical service providers, such as PCPs wishing to enter into risk-bearing contracts, could utilize the tools contained in this research to construct various models to predict the results given various assumptions about patient attributes, services utilization, and compensation schemes (such as capitation and risk pools). They could enter the profiles of their existing Medicare patients and the profiles of incremental patients they anticipate receiving from participation in new agreements with MAO. These analyses could be very instructive to providers when deciding to accept or reject participation agreements from MAOs or negotiating better terms for agreements that interest them.

Specialist referrals. Our research only examines the total volumes of general category services used by beneficiaries of RB PCPs and FFS PCPs. Researchers could utilize the provider identifiers, taxonomy codes, service centers, and associated volumes to determine if there is a significant difference in the mix and quantity of services within each category used by beneficiaries of RB PCPs and FFS PCPs. Those results, compared with results found in the PCP practice-based services research, might uncover meaningful correlations between PCP practices and specialist referrals.

Service mix by plan. Researchers could examine the mix of services used by beneficiaries for each unique plan and benefits structure. Among other potential findings, researchers may discover that some MAO plans offer a broader selection of lower-cost services while other plans offer a narrower selection of higher-cost services. Included in this type of research would be the amount of the patient's deductible and co-payment responsibilities as potential explanatory variables in plan and benefit selections.

Clinical outcomes. Our brief discussion of quality, including clinical outcomes, highlights a concern that the industry struggles with this element of patient care evaluation. Researchers could assess the ongoing debate about clinical outcomes and quality metrics, devise appropriate variables, extract the corresponding values from the Medicare files, and utilize the methods shown in this study to determine what relationships exist among those variables. Death rates, readmission rates, and alternative measures for changes in health status can be examined with information in the CMS datasets. Associations between patient characteristics, plan choice, provider access, physician compensation structures and clinical outcomes would provide useful perspective as participating parties collaborate in efforts to improve healthcare delivery.

Health status. Researchers could replace the CCMI score with an alternative variable to determine if health status defined differently has a different relationship to services utilization than shown in our research.

Access to care. There may be alternative proxies for access to hospitals and doctors. Refinements could be made by examining the effects of the availability of specific physician specialties, clinics, and hospital types. Also, consideration could be given to service availability in neighboring counties or regions. Transportation modes (e.g., auto, public transportation, taxi) may affect access to health care service locations. More recently, because of the Covid-19 pandemic, CMS has lifted several restrictions on the use of telemedicine. The removal of physical barriers made possible by digital transmission of conversations and images could have an effect on service utilization; however, some beneficiaries may not have access to the necessary technology to access those services. Consequently, future research could investigate these and other potential barriers that beneficiaries encounter when trying to access the health services that they require.

Longitudinal studies. As data integrity improves, and CMS releases more years of data, researchers could identify longer-term patterns and trends of healthcare services used by Medicare beneficiaries. Beneficiaries could be grouped into various subsets to examine the effects of physician and plan choices over time. Policymakers could better evaluate their strategy to steer Medicare beneficiaries into Medicare Advantage plans. Also, by examining clinical outcomes derived from the data, more careful analyses could be conducted to determine if there are differences in the long-term clinical outcomes of Traditional Medicare and MA beneficiaries. Researchers could also look for evolution in plan choices as driven by beneficiary attributes or industry changes.

6.5 Conclusion

Our study found that personal traits, access to providers, and levels of wealth and education, exhibit statistically significant relationships with a beneficiary's choice of Medicare plans. Using statistical methods such as CHAID decision trees and Poisson regression, we show how those attributes (personal traits, access, wealth, education, and plan choice) also predict service utilization in each of five general categories: inpatient admissions, skilled nursing admissions, outpatient services, home health services, and carrier services.

We identified major stakeholders in the Medicare system, demonstrated how they preside as both principal and agent, and discussed their operational problems predicted by agency theory. By conducting fieldwork that included discussions with PCPs and MAOs and reviews of their participation agreements, we were able to identify the elements of purportedly successful contract terms that serve to mitigate the problems posed by agency theory. A review of results stemming from one such contract suggests that beneficiaries of MAOs engaged with RB PCPs will utilize fewer healthcare resources than beneficiaries in FFS plans and, possibly, those in other HMO plans. This is an area for further exploration. Overall, our findings suggest that the features of health insurance plans and compensation mechanisms for healthcare providers significantly affect the services received by individual patients. Quantifying the impact of these effects with the methods used in this dissertation can provide vital information to governmental officials, health insurers, healthcare organizations and individual practitioners.

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Appendix A: Risk-bearing Contracts for Primary Care Physicians

Typically, Managed Care Organizations (MAOs) receive a monthly payment, sometimes referred to as capitation, from CMS for each insured member in the MAO's Medicare Advantage plan(s) assigned to a physician or physician group. The capitation payment emanates from a complex formula that includes, but is not limited to, such variables as the MAO's bid amount sent to CMS; the insured patient's age, sex, geographic location, place of residence and other demographics; risk adjustments for health conditions; prior year adjustments that are posted in the current year; and incentive payments based on the plan's performance as indicated by the plan's prior-year "Star" rating. Due to these variables, monthly capitation payments will differ from patient to patient. The complexities of this risk-adjusted payment structure are not addressed in this paper, but they can be reviewed in detail at CMS' website at www.cms.gov. For our purposes, we shall refer to the CMS payment as the average risk-adjusted capitation payment received for each insured member. We label this monthly capitation payment as "*C*."

The MAO generally retains a portion of the *C* to fund its internal resources such as general management, provider contracting and relations, marketing, sales, advertising, information technology, other administrative functions, and potential profits. The retention typically is a percentage of *C*. We label the retention percentage as "*r*." The difference between *C* and *(C * r)* is the pool of dollars available to pay all medical and medically related expenses for the care of the insured member (patient). We label this pool as "*P*."

$$[C – (C * r)] = P$$

Medical and medically related expenses include payments to hospitals, doctors, ancillary service providers, laboratories, pharmacies, outpatient surgery centers, home health companies, member/patient health club memberships, stop-loss reinsurance companies, and other costs of care and services. We label the average expenses per patient as "*E*." If $P > E$, then there is a surplus in the pool. If $P < E$, there is a deficit. If $P = E$, the pool has a zero balance. During contract negotiations, the PCP Organization (PCP) and MAO negotiate each party's respective share of the surplus or deficit, and the terms of those negotiations are written into the contract between the parties. If there is a surplus, the contract requires the MAO to pay the PCPs' share of the surplus to the PCPs within a specified period. If there is a deficit, the contract requires the PCPs to pay their share of the deficit to the MAO within a specified period. Alternatively, the PCPs and the MAO may agree to provisions whereby current deficit payments due from the PCPs are deducted from PCPs' future surpluses, thus reducing those future payments, but easing the PCPs' near-term cash flow burden.

There also can be variations in this payment methodology. In recent years, it is our observation that agreements between MAOs and PCPs have become increasingly complex, especially regarding the calculations for both surplus/deficit sharing and supplemental incentives such as the outcomes measures. For example, the contract between the PCPs and a MAO might state that the ratio value of *E* to *P* (*E/P*) must be less than a specific threshold to qualify for financial incentives. Alternatively, if *E/P* equals or exceeds the threshold, then the PCPs may incur financial penalties. In this type of arrangement, the MAO expects the overall cost of care to be such that *E/P* is less than a predefined ratio, denoted by "*X*". Thus, we can write:

If E/P < X, then then PCPs receive a share of the surplus
If E/P > X, then the PCPs' share of the surplus is voided and penalties are incurred

Our experience suggests that the PCPs' share of surpluses (and deficits) ranges from 60% to 80% in these types of risk-bearing arrangements. We label the PCPs' percentage share as "*S*"; therefore, we can write:

$[C – (C * r)] = P$
If E/P < X, then the PCP share of surplus = $[(P * X) – E] * S$
If E/P ≥ X, then the PCP repayment to MAO = $[(P * X) – E] * S$

The *X* may or may not be negotiable, and may reflect past precedent or the parties' goals for the upcoming contract year(s), or both.

In addition to financial incentives, contracts between MAOs and PCPs also may contain outcomes incentives. Our experience with and review of Medicare Advantage contracts between MAOs and PCPs suggests that outcomes incentives are calculated differently in each contract based on the MAO's objectives. Generally, it appears that outcomes incentives are directly related to the MAO's effort to maximize its Star rating. Outcomes metrics contained in the Star rating program for MAOs, and the outcomes incentives for PCPs, are derived, in part, from a listing of measures included in the **Healthcare Effectiveness Data and Information Set (HEDIS)**, one of the most widely used sets of health care performance measures in the United States (NCQA, 2018). This information is collected, compiled, and published by the non-profit organization, National Committee for Quality Assurance (NCQA). Background information about NCQA and HEDIS is available at www.ncqa.org.

Based on our conversations with MAOs and Harmony PCPs, we believe that outcomes metrics achievement or non-achievement are introduced into the payment model for at least four reasons: a) to create a critical check and balance offering deterrence, in the form of opportunity costs, for underutilization of resources, resulting in lower *E*, that potentially would harm members/patients, b) to help the MAO maximize its CMS Star rating, c) to provide guidance and structure that assist PCPs in efforts to improve clinical outcomes, and d) to reward PCPs for improving outcomes. Our review of MAOs' contracts with PCPs indicates that achievement of specified benchmarks, either individually or collectively, is rewarded as dollar payments that supplement the PCPs' surplus share, or as additional percentages added to S, with either method resulting in a potentially higher rate of compensation than offered by a financial incentive alone.

The outcomes incentives may be expressed as a pre-defined dollar value per outcome attained, or a pre-defined percentage value that supplements *S*. We let i_j be the predefined dollar incentive for outcome j, i'_j be the predefined percentage incentive for outcome j, and $\alpha_j = 1$ if outcome j is attained, and 0 otherwise. We illustrate the effects outcomes incentives have on payment models with three hypothetical risk-bearing contracts, as follows:

Scenario 1. Assumptions: *E/P* ratio is favorable (i.e., less than *X)*, and n dollar incentive measures are available to supplement the surplus share.

*Given [C – (C * r)] = P, and E/P < X,*
*Therefore, PCP Earnings = {[(P * X) – E] * S} +* $\sum_{j=1}^{n} \alpha_j * i_j$

Scenario 2. Assumptions: *E/P* ratio is unfavorable *(i.e., E/P ≥ X), but* n dollar incentive measures are available to help offset the penalty for not achieving the ratio *X*.

*Given [C – (C * r)] = P, and E/P ≥ X,*

*Therefore, PCP Earnings = {[(P * X) – E] * S}* + $\sum_{j=1}^{n} \alpha_j * i_j$ *(a potential deficit)*

Scenario 3. Assumptions: The contract terms do not include a threshold (*X*), but n percentage incentive measures are available to supplement *S*.

*Given [C – (C * r)] = P and P > E*

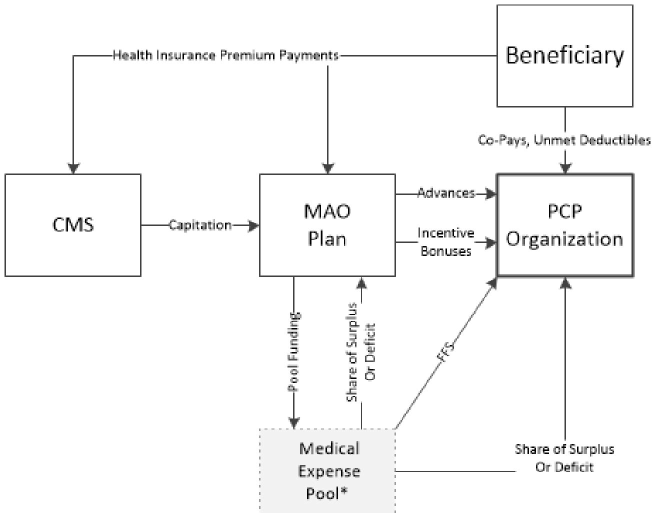
*Therefore, PCP Earnings = (P – E) * (S +* $\sum_{j=1}^{n} \alpha_j * i'_j$ *)*

We note that these payment formulas generally are not calculated for each patient. Instead, it is typically the summation of payments, expenses, and incentives for the entire patient panel assigned to each PCP or the entire PCP group.

The MAO typically makes these calculations and reports them to the PCPs on a monthly, quarterly, and annual basis. Cumulative calculations sometimes are titled “reconciliations” and typically occur on quarterly and yearly bases several weeks after the close of those respective periods. This delayed reporting allows for “incurred but not reported claims” (IBNR) to make their way into the MAO’s payment system before the reconciliations.

The previously displayed Exhibit 7 illustrates the flow of funds for the various components of a generic Medicare Advantage risk-bearing contract between an MAO and PCP group organized to enter into such agreements. Our discussions with Harmony physicians and reviews of their risk-bearing contracts inform us that Harmony PCPs may generate revenue from any or all of five different sources: 1) advance from the MAO, 2) FFS reimbursement for medical services rendered, 3) the share of the medical expense pool surplus, 4) outcomes incentives earned, and 5) patient co-payments and unmet deductibles (see Exhibit A1).

Exhibit A1. MA-HMO Funds Flow



*For payment of services provided by Physicians (PCPs and Specialists), Hospitals and Other Facilities, Ancillary Service Providers, Durable Medical Equipment, Home Healthcare, Pharmacies, Re-insurance Premiums, Etc.

It is the summation of these five revenue sources that PCPs compare and contrast to Traditional Medicare fee-for-service arrangements to determine if the financial reward from MA-HMO participation justifies the risks incurred.

For illustrative and simplicity purposes, we shall examine the hypothetical results for a single patient/member for one month, using the three scenarios described previously. We use the following common data for all scenarios:

C (Monthly Capitation Payment) = $1,000

r (MAO Retention) = 10%

i_1 (Dollar outcomes metric) = $1.00

i_2 (Dollar outcomes metric) = $1.50

i_3 (Dollar outcomes metric) = $1.50

i_4 (Dollar outcomes metric) = $2.00

i_5 (Dollar outcomes metric) = $2.00

i_6 (Dollar outcomes metric) = $2.50

i'_1 (Percentage outcomes metric) = 1.0%

i'_2 (Percentage outcomes metric) = 1.5%

i'_3 (Percentage outcomes metric) = 1.5%

i'_4 (Percentage outcomes metric) = 2.0%

i'_5 (Percentage outcomes metric) = 2.0%

i'_6 (Percentage outcomes metric) = 3.0%

In each scenario, the calculated pool P = [1,000 – (1,000 * 0.1)] = $900

Scenario 1. Assumptions: *E/P* ratio is favorable (i.e., less than *X)*, and all six dollar amount outcomes incentive measures are achieved. Let:

E (Medical Expense) = $700

X (Expense Threshold) = 85%

S (PCP Share) = 75%

Then:

PCP Earnings = {[(900 * 0.85) – 700)] * 0.75} + {1.00 + 1.50 + 1.50 + 2.00 +2.00 + 2.50}

= {48.75} + {10.50}

= 59.25, or $59.25 payment for one patient, for one month

If one were to assume that a PCP has a panel of 150 patients of comparable demographics and health, and the results were the same each month of the year for each patient, then the PCP's earnings would be as follows:

$59.25/month/patient * 150 patients * 12 months/year = $106,650 annually

Scenario 2. Assumptions: *E/P* ratio is unfavorable *(i.e., E/P ≥ X), but* all six dollar outcomes incentive measures are achieved to offset the penalty for the *E/P* ratio not exceeding *X*.

Let:

E (Medical Expense) = $800

X (Expense Threshold) = 85%

S (PCP Share) = 75%

Then:

PCP Earnings = {[(900 * 0.85) – 800)] * 0.75} + {1.00 + 1.50 + 1.50 + 2.00 +2.00 + 2.50}

= {-26.25} + {10.50}

= -15.75, or -$15.75 for one patient, for one month (to be repaid to the MAO)

If one were to assume that a PCP has a panel of 150 patients of comparable demographics and health (i.e., comparable risk factors), and the results were the same each month of the year for each patient, then the PCP's earnings would be as follows:

-$15.75/month/patient * 150 patients * 12 months/year = -$28,350 annually (payable to MAO)

In this scenario, the PCP provided services to a patient panel for one year but had to reimburse the MAO for the shortfall. Further analysis would be needed to determine if the PCP incurred an overall net loss because other payment sources such as patient co-pays and services paid on a fee-for-service basis could potentially offset some or all of the loss, and possibly return the PCP to a net positive result.

Scenario 3. Assumptions: The contract does not contain a threshold (*X*), and the PCP surplus share percentage *S* is increased due to the achievement of all six percentage outcomes measures to supplements *S*.

Let:

E (Medical Expense) = $750

S (PCP Share) = 60%

Then:

PCP Earnings = (900 – 750) * (0.60 + 0.01 + 0.015 + 0.015 + 0.02 + 0.02 +0.025)

= (150) * (0.705)

= 105.75, or $105.75 payment for one patient, for one month

If one were to assume that a PCP has a panel of 150 patients each having comparable risk factors, and the results were the same each month of the year for each patient, then the PCP’s earnings would be as follows:

$105.75/month/patient * 150 patients * 12 months/year = $190,350 annually

Of course, these illustrations overly simplify the actual contract terms and conditions, as well as the amount of data generated and resultant calculations, attributable to the 150 patients of varying demographics and illnesses contained in an actual reconciliation process.

In addition to financial and outcomes measures, we observe other types of incentives incorporated into these risk-bearing contracts. Examples include cash rewards for patient satisfaction survey results (MAOs desire high ratings) and utilization metrics (MAOs want reduced utilization) such as hospital inpatient days per thousand patients and hospital emergency department visits per thousand patients. Further complexity occurs when some contracts prescribe an advance payment to the PCPs as interim cash flow support before reconciliation payments. These advance payments pose an additional risk component because some or the entire advance would have to be repaid to the MAO should the PCPs find themselves in a deficit position at reconciliation. Advance payment also creates a cash management dilemma: should the advance be recognized as spendable income, or should it be reserved for losses? The Harmony PCPs told us they install a measure of both by using an internal risk share methodology that establishes an internal reserve that offsets future deficits. If the reserve is not used by year-end, the proceeds are distributed to the PCPs per a pre-defined formula.

These scenarios demonstrate the tremendous importance of PCPs familiarizing themselves, and acting on, the information supplied by the MAO, but also received from multiple sources: CMS, NCQA, contract terms and conditions, provider claims and payment data, historical records, outcomes data, and other informational sources. When Harmony PCPs discuss their risks inherent in these types of risk bearing (RB) arrangements, they frequently mention that their total compensation as Medicare Advantage HMO participating physicians is heavily dependent on several factors, some controllable, some not. From our field observations, we note that the Harmony PCPs place substantial reliance on the MAOs to supply timely and useful information to help the PCPs perform well. To get more contemporary and customized data, some PCP groups invest in specialized technology and services to supplement the MAOs' information.

Collectively, many elements comprise the payment scheme that attempts to incentivize and compensate PCPs for the care of Medicare Advantage beneficiaries assigned to them. Our interaction with the Harmony PCPs left us quite impressed with their ability to analyze data and understand the extent to which various elements pose a financial risk and therefore impact their payments from MAOs. However, the complexity of these arrangements also makes one mindful of the significant body of knowledge a fee-for-service-oriented PCP, or PCP group should possess before committing to a Medicare Advantage risk-bearing contract. Additionally, the PCPs should ensure their contract negotiator has experience with such contract complexities.

Appendix B: Master Beneficiary Summary File Variables and Names

SAS Name	Label	Type	Length
Base Claim File:			
BENE_ID	Encrypted CCW Beneficiary ID	CHAR	15
BENE_ENROLLMT_REF_YR	Reference Year	NUM	4
ENRL_SRC	Source of enrollment data	CHAR	3
SAMPLE_GROUP	Medicare 1, 5, or 20% strict sample group indicator	CHAR	2
ENHANCED_FIVE_PERCENT_FLAG	Enhanced Medicare 5% Sample Indicator	CHAR	1
CRNT_BIC_CD	Current Beneficiary Identification Code	CHAR	2
STATE_CODE	State code for beneficiary (SSA code)	CHAR	2
COUNTY_CD	County code for beneficiary (SSA code)	CHAR	3
ZIP_CD	5-digit ZIP code for beneficiary	CHAR	5
STATE_CNTY_FIPS_CD_01	State and county FIPS code - January	CHAR	5
STATE_CNTY_FIPS_CD_02	State and county FIPS code - February	CHAR	5
STATE_CNTY_FIPS_CD_03	State and county FIPS code - March	CHAR	5
STATE_CNTY_FIPS_CD_04	State and county FIPS code - April	CHAR	5
STATE_CNTY_FIPS_CD_05	State and county FIPS code - May	CHAR	5
STATE_CNTY_FIPS_CD_06	State and county FIPS code - June	CHAR	5
STATE_CNTY_FIPS_CD_07	State and county FIPS code - July	CHAR	5
STATE_CNTY_FIPS_CD_08	State and county FIPS code - August	CHAR	5
STATE_CNTY_FIPS_CD_09	State and county FIPS code - September	CHAR	5
STATE_CNTY_FIPS_CD_10	State and county FIPS code - October	CHAR	5
STATE_CNTY_FIPS_CD_11	State and county FIPS code - November	CHAR	5
STATE_CNTY_FIPS_CD_12	State and county FIPS code - December	CHAR	5
AGE_AT_END_REF_YR	Age of beneficiary at end of year	NUM	3
BENE_BIRTH_DT	Beneficiary date of birth	DATE	8
VALID_DEATH_DT_SW	Valid Date of Death Switch	CHAR	1
BENE_DEATH_DT	Date of Death	DATE	8
SEX_IDENT_CD	Sex	CHAR	1
BENE_RACE_CD	Beneficiary Race Code	CHAR	1
RTI_RACE_CD	Research Triangle Institute (RTI) Race Code	CHAR	1
COVSTART	Medicare Coverage Start Date	DATE	8
ENTLMT_RSN_ORIG	Original Reason for Entitlement Code	CHAR	1
ENTLMT_RSN_CURR	Current Reason for Entitlement Code	CHAR	1
ESRD_IND	End-stage Renal Disease (ESRD) Indicator	CHAR	1
MDCR_STATUS_CODE_01	Medicare Status Code - January	CHAR	2
MDCR_STATUS_CODE_02	Medicare Status Code - February	CHAR	2
MDCR_STATUS_CODE_03	Medicare Status Code - March	CHAR	2
MDCR_STATUS_CODE_04	Medicare Status Code - April	CHAR	2
MDCR_STATUS_CODE_05	Medicare Status Code - May	CHAR	2
MDCR_STATUS_CODE_06	Medicare Status Code - June	CHAR	2

MDCR_STATUS_CODE_07	Medicare Status Code - July	CHAR	2
MDCR_STATUS_CODE_08	Medicare Status Code - August	CHAR	2
MDCR_STATUS_CODE_09	Medicare Status Code - September	CHAR	2
MDCR_STATUS_CODE_10	Medicare Status Code - October	CHAR	2
MDCR_STATUS_CODE_11	Medicare Status Code - November	CHAR	2
MDCR_STATUS_CODE_12	Medicare Status Code - December	CHAR	2
BENE_PTA_TRMNTN_CD	Part A Termination Code	CHAR	1
BENE_PTB_TRMNTN_CD	Part B Termination Code	CHAR	1
BENE_HI_CVRAGE_TOT_MONS	Part A Months Count	NUM	3
BENE_SMI_CVRAGE_TOT_MONS	Part B Months Count	NUM	3
BENE_STATE_BUYIN_TOT_MONS	State Buy-In Coverage Count	NUM	3
BENE_HMO_CVRAGE_TOT_MONS	HMO Coverage Count	NUM	3
PTD_PLAN_CVRG_MONS	Months of Part D Coverage	NUM	3
RDS_CVRG_MONS	Months of Retiree Drug Subsidy Coverage	NUM	3
DUAL_ELGBL_MONS	Months of Dual Eligibility	NUM	3
MDCR_ENTLMT_BUYIN_IND_01	Medicare Entitlement/Buy-In Indicator - January	CHAR	1
MDCR_ENTLMT_BUYIN_IND_02	Medicare Entitlement/Buy-In Indicator - February	CHAR	1
MDCR_ENTLMT_BUYIN_IND_03	Medicare Entitlement/Buy-In Indicator - March	CHAR	1
MDCR_ENTLMT_BUYIN_IND_04	Medicare Entitlement/Buy-In Indicator - April	CHAR	1
MDCR_ENTLMT_BUYIN_IND_05	Medicare Entitlement/Buy-In Indicator - May	CHAR	1
MDCR_ENTLMT_BUYIN_IND_06	Medicare Entitlement/Buy-In Indicator - June	CHAR	1
MDCR_ENTLMT_BUYIN_IND_07	Medicare Entitlement/Buy-In Indicator - July	CHAR	1
MDCR_ENTLMT_BUYIN_IND_08	Medicare Entitlement/Buy-In Indicator - August	CHAR	1
MDCR_ENTLMT_BUYIN_IND_09	Medicare Entitlement/Buy-In Indicator - September	CHAR	1
MDCR_ENTLMT_BUYIN_IND_10	Medicare Entitlement/Buy-In Indicator - October	CHAR	1
MDCR_ENTLMT_BUYIN_IND_11	Medicare Entitlement/Buy-In Indicator - November	CHAR	1
MDCR_ENTLMT_BUYIN_IND_12	Medicare Entitlement/Buy-In Indicator - December	CHAR	1
HMO_IND_01	HMO Indicator - January	CHAR	1
HMO_IND_02	HMO Indicator - February	CHAR	1
HMO_IND_03	HMO Indicator - March	CHAR	1
HMO_IND_04	HMO Indicator - April	CHAR	1
HMO_IND_05	HMO Indicator - May	CHAR	1
HMO_IND_06	HMO Indicator - June	CHAR	1
HMO_IND_07	HMO Indicator - July	CHAR	1
HMO_IND_08	HMO Indicator - August	CHAR	1
HMO_IND_09	HMO Indicator - September	CHAR	1
HMO_IND_10	HMO Indicator - October	CHAR	1

HMO_IND_11	HMO Indicator - November	CHAR	1
HMO_IND_12	HMO Indicator - December	CHAR	1
PTC_CNTRCT_ID_01	Part C Contract Number - January	CHAR	5
PTC_CNTRCT_ID_02	Part C Contract Number - February	CHAR	5
PTC_CNTRCT_ID_03	Part C Contract Number - March	CHAR	5
PTC_CNTRCT_ID_04	Part C Contract Number - April	CHAR	5
PTC_CNTRCT_ID_05	Part C Contract Number - May	CHAR	5
PTC_CNTRCT_ID_06	Part C Contract Number - June	CHAR	5
PTC_CNTRCT_ID_07	Part C Contract Number - July	CHAR	5
PTC_CNTRCT_ID_08	Part C Contract Number - August	CHAR	5
PTC_CNTRCT_ID_09	Part C Contract Number - September	CHAR	5
PTC_CNTRCT_ID_10	Part C Contract Number - October	CHAR	5
PTC_CNTRCT_ID_11	Part C Contract Number - November	CHAR	5
PTC_CNTRCT_ID_12	Part C Contract Number - December	CHAR	5
PTC_PBP_ID_01	Part C PBP Number - January	CHAR	3
PTC_PBP_ID_02	Part C PBP Number - February	CHAR	3
PTC_PBP_ID_03	Part C PBP Number - March	CHAR	3
PTC_PBP_ID_04	Part C PBP Number - April	CHAR	3
PTC_PBP_ID_05	Part C PBP Number - May	CHAR	3
PTC_PBP_ID_06	Part C PBP Number - June	CHAR	3
PTC_PBP_ID_07	Part C PBP Number - July	CHAR	3
PTC_PBP_ID_08	Part C PBP Number - August	CHAR	3
PTC_PBP_ID_09	Part C PBP Number - September	CHAR	3
PTC_PBP_ID_10	Part C PBP Number - October	CHAR	3
PTC_PBP_ID_11	Part C PBP Number - November	CHAR	3
PTC_PBP_ID_12	Part C PBP Number - December	CHAR	3
PTC_PLAN_TYPE_CD_01	Part C Plan Type Code - January	CHAR	3
PTC_PLAN_TYPE_CD_02	Part C Plan Type Code - February	CHAR	3
PTC_PLAN_TYPE_CD_03	Part C Plan Type Code - March	CHAR	3
PTC_PLAN_TYPE_CD_04	Part C Plan Type Code - April	CHAR	3
PTC_PLAN_TYPE_CD_05	Part C Plan Type Code - May	CHAR	3
PTC_PLAN_TYPE_CD_06	Part C Plan Type Code - June	CHAR	3
PTC_PLAN_TYPE_CD_07	Part C Plan Type Code - July	CHAR	3
PTC_PLAN_TYPE_CD_08	Part C Plan Type Code - August	CHAR	3
PTC_PLAN_TYPE_CD_09	Part C Plan Type Code - September	CHAR	3
PTC_PLAN_TYPE_CD_10	Part C Plan Type Code - October	CHAR	3
PTC_PLAN_TYPE_CD_11	Part C Plan Type Code - November	CHAR	3
PTC_PLAN_TYPE_CD_12	Part C Plan Type Code - December	CHAR	3
PTD_CNTRCT_ID_01	Part D Contract Number - January	CHAR	5
PTD_CNTRCT_ID_02	Part D Contract Number - February	CHAR	5
PTD_CNTRCT_ID_03	Part D Contract Number - March	CHAR	5
PTD_CNTRCT_ID_04	Part D Contract Number - April	CHAR	5
PTD_CNTRCT_ID_05	Part D Contract Number - May	CHAR	5
PTD_CNTRCT_ID_06	Part D Contract Number - June	CHAR	5
PTD_CNTRCT_ID_07	Part D Contract Number - July	CHAR	5

PTD_CNTRCT_ID_08	Part D Contract Number - August	CHAR	5
PTD_CNTRCT_ID_09	Part D Contract Number - September	CHAR	5
PTD_CNTRCT_ID_10	Part D Contract Number - October	CHAR	5
PTD_CNTRCT_ID_11	Part D Contract Number - November	CHAR	5
PTD_CNTRCT_ID_12	Part D Contract Number - December	CHAR	5
PTD_PBP_ID_01	Part D PBP Number - January	CHAR	3
PTD_PBP_ID_02	Part D PBP Number - February	CHAR	3
PTD_PBP_ID_03	Part D PBP Number - March	CHAR	3
PTD_PBP_ID_04	Part D PBP Number - April	CHAR	3
PTD_PBP_ID_05	Part D PBP Number - May	CHAR	3
PTD_PBP_ID_06	Part D PBP Number - June	CHAR	3
PTD_PBP_ID_07	Part D PBP Number - July	CHAR	3
PTD_PBP_ID_08	Part D PBP Number - August	CHAR	3
PTD_PBP_ID_09	Part D PBP Number - September	CHAR	3
PTD_PBP_ID_10	Part D PBP Number - October	CHAR	3
PTD_PBP_ID_11	Part D PBP Number - November	CHAR	3
PTD_PBP_ID_12	Part D PBP Number - December	CHAR	3
PTD_SGMT_ID_01	Part D Segment Number - January	CHAR	3
PTD_SGMT_ID_02	Part D Segment Number - February	CHAR	3
PTD_SGMT_ID_03	Part D Segment Number - March	CHAR	3
PTD_SGMT_ID_04	Part D Segment Number - April	CHAR	3
PTD_SGMT_ID_05	Part D Segment Number - May	CHAR	3
PTD_SGMT_ID_06	Part D Segment Number - June	CHAR	3
PTD_SGMT_ID_07	Part D Segment Number - July	CHAR	3
PTD_SGMT_ID_08	Part D Segment Number - August	CHAR	3
PTD_SGMT_ID_09	Part D Segment Number - September	CHAR	3
PTD_SGMT_ID_10	Part D Segment Number - October	CHAR	3
PTD_SGMT_ID_11	Part D Segment Number - November	CHAR	3
PTD_SGMT_ID_12	Part D Segment Number - December	CHAR	3
RDS_IND_01	Part D Retiree Drug Subsidy Indicator - January	CHAR	1
RDS_IND_02	Part D Retiree Drug Subsidy Indicator - February	CHAR	1
RDS_IND_03	Part D Retiree Drug Subsidy Indicator - March	CHAR	1
RDS_IND_04	Part D Retiree Drug Subsidy Indicator - April	CHAR	1
RDS_IND_05	Part D Retiree Drug Subsidy Indicator - May	CHAR	1
RDS_IND_06	Part D Retiree Drug Subsidy Indicator - June	CHAR	1
RDS_IND_07	Part D Retiree Drug Subsidy Indicator - July	CHAR	1
RDS_IND_08	Part D Retiree Drug Subsidy Indicator - August	CHAR	1
RDS_IND_09	Part D Retiree Drug Subsidy Indicator - September	CHAR	1
RDS_IND_10	Part D Retiree Drug Subsidy Indicator - October	CHAR	1

RDS_IND_11	Part D Retiree Drug Subsidy Indicator - November	CHAR	1
RDS_IND_12	Part D Retiree Drug Subsidy Indicator - December	CHAR	1
DUAL_STUS_CD_01	Medicare-Medicaid dual eligibility code - January	CHAR	2
DUAL_STUS_CD_02	Medicare-Medicaid dual eligibility code - February	CHAR	2
DUAL_STUS_CD_03	Medicare-Medicaid dual eligibility code - March	CHAR	2
DUAL_STUS_CD_04	Medicare-Medicaid dual eligibility code - April	CHAR	2
DUAL_STUS_CD_05	Medicare-Medicaid dual eligibility code - May	CHAR	2
DUAL_STUS_CD_06	Medicare-Medicaid dual eligibility code - June	CHAR	2
DUAL_STUS_CD_07	Medicare-Medicaid dual eligibility code - July	CHAR	2
DUAL_STUS_CD_08	Medicare-Medicaid dual eligibility code - August	CHAR	2
DUAL_STUS_CD_09	Medicare-Medicaid dual eligibility code - September	CHAR	2
DUAL_STUS_CD_10	Medicare-Medicaid dual eligibility code - October	CHAR	2
DUAL_STUS_CD_11	Medicare-Medicaid dual eligibility code - November	CHAR	2
DUAL_STUS_CD_12	Medicare-Medicaid dual eligibility code - December	CHAR	2
CST_SHR_GRP_CD_01	Part D low-income cost share group code - January	CHAR	2
CST_SHR_GRP_CD_02	Part D low-income cost share group code - February	CHAR	2
CST_SHR_GRP_CD_03	Part D low-income cost share group code - March	CHAR	2
CST_SHR_GRP_CD_04	Part D low-income cost share group code - April	CHAR	2
CST_SHR_GRP_CD_05	Part D low-income cost share group code - May	CHAR	2
CST_SHR_GRP_CD_06	Part D low-income cost share group code - June	CHAR	2
CST_SHR_GRP_CD_07	Part D low-income cost share group code - July	CHAR	2
CST_SHR_GRP_CD_08	Part D low-income cost share group code - August	CHAR	2
CST_SHR_GRP_CD_09	Part D low-income cost share group code - September	CHAR	2
CST_SHR_GRP_CD_10	Part D low-income cost share group code - October	CHAR	2
CST_SHR_GRP_CD_11	Part D low-income cost share group code - November	CHAR	2
CST_SHR_GRP_CD_12	Part D low-income cost share group code - December	CHAR	2

Appendix C: Inpatient and Skilled Nursing Variables and Names

SAS Name	Label	Type	Length	2015
Base Claim File				
BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
SAMPLE_GROUP	CCW Beneficiary Random Sample Group	Char	2	2
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	3
CLM_TYPE_CD	Claim Type Code	Char	4	4
CLM_FROM_DT	Claim From Date	Date	8	5
CLM_THRU_DT	Claim Through Date	Date	8	6
SRVC_MONTH	Service Month	Date	6	7
CLM_CHRT_RVW_SW	Claim Chart Review Switch	Char	1	8
CLM_CNTL_NUM	Claim Control Number	Char	23	9
CLM_ORIG_CNTL_NUM	Claim Original Control Number	Char	23	10
CLM_FINL_ACTN_IND	Claim Final Action Indicator	Char	1	11
CLM_LTST_CLM_IND	Latest Claim Indicator	Char	1	12
EDPS_CREATE_DT	Encounter Data Processing System (EDPS) Create Date	Date	8	13
CLM_RCPT_DT	Claim Receipt Date	Date	8	14
CLM_FAC_TYPE_CD	Claim Facility Type Code	Char	1	15
CLM_SRVC_CLSFCTN_TYPE_CD	Claim Service classification Type Code	Char	1	16
CLM_FREQ_CD	Claim Frequency Code	Char	1	17
CNTRCT_NUM	Medicare Part C Contract Number	Char	5	18
CNTRCT_PBP_NUM	Medicare Part C Plan Benefit Package (PBP) Number	Char	3	19
CLM_MDCL_REC	Claim Medical Record Number	Char	1	20
ORG_NPI	Organization NPI Number	Char	10	21
ORG_TXNMY_CD	Organization Taxonomy Code	Char	10	22
RNDRNG_PHYSN_NPI	Claim Rendering Physician NPI Number	Char	10	23
AT_PHYSN_NPI	Claim Attending Physician NPI Number	Char	10	24
AT_PHYSN_TXNMY_CD	Claim Attending Physician Taxonomy Code	Char	10	25
OP_PHYSN_NPI	Claim Operating Physician NPI Number	Char	10	26
OT_PHYSN_NPI	Claim Other Physician NPI Number	Char	10	27
CLM_ADMSN_DT	Claim Admission Date	Date	8	28
CLM_IP_ADMSN_TYPE_CD	Claim Inpatient Admission Type Code	Char	1	29
CLM_SRC_IP_ADMSN_CD	Claim Source Inpatient Admission Code	Char	1	30
PTNT_DSCHRG_STUS_CD	Patient Discharge Status Code	Char	2	31
CLM_DAY_CNT	Day Count (Length of Stay)	Num	4	32
BENE_DSCHRG_DT	Beneficiary Discharge Date	Date	8	33
CLM_DRG_CD	Claim MS-Diagnosis Related Group Code (MS-DRG)	Char	3	34
DRVD_DRG_CD	Derived MS-Diagnosis Related Group Code (MS-DRG)	Char	4	35
ADMTG_DGNS_CD	Claim Admitting Diagnosis Code	Char	7	36
PRNCPAL_DGNS_CD	Claim Principal Diagnosis Code	Char	7	37
ICD_DGNS_CD1	Claim Diagnosis Code 1	Char	7	38
ICD_DGNS_CD2	Claim Diagnosis Code 2	Char	7	39
ICD_DGNS_CD3	Claim Diagnosis Code 3	Char	7	40

ICD_DGNS_CD4	Claim Diagnosis Code 4	Char	7	41
ICD_DGNS_CD5	Claim Diagnosis Code 5	Char	7	42
ICD_DGNS_CD6	Claim Diagnosis Code 6	Char	7	43
ICD_DGNS_CD7	Claim Diagnosis Code 7	Char	7	44
ICD_DGNS_CD8	Claim Diagnosis Code 8	Char	7	45
ICD_DGNS_CD9	Claim Diagnosis Code 9	Char	7	46
ICD_DGNS_CD10	Claim Diagnosis Code 10	Char	7	47
ICD_DGNS_CD11	Claim Diagnosis Code 11	Char	7	48
ICD_DGNS_CD12	Claim Diagnosis Code 12	Char	7	49
ICD_DGNS_CD13	Claim Diagnosis Code 13	Char	7	50
ICD_DGNS_CD14	Claim Diagnosis Code 14	Char	7	51
ICD_DGNS_CD15	Claim Diagnosis Code 15	Char	7	52
ICD_DGNS_CD16	Claim Diagnosis Code 16	Char	7	53
ICD_DGNS_CD17	Claim Diagnosis Code 17	Char	7	54
ICD_DGNS_CD18	Claim Diagnosis Code 18	Char	7	55
ICD_DGNS_CD19	Claim Diagnosis Code 19	Char	7	56
ICD_DGNS_CD20	Claim Diagnosis Code 20	Char	7	57
ICD_DGNS_CD21	Claim Diagnosis Code 21	Char	7	58
ICD_DGNS_CD22	Claim Diagnosis Code 22	Char	7	59
ICD_DGNS_CD23	Claim Diagnosis Code 23	Char	7	60
ICD_DGNS_CD24	Claim Diagnosis Code 24	Char	7	61
ICD_DGNS_CD25	Claim Diagnosis Code 25	Char	7	62
CLM_POA_IND_SW1	Claim Diagnosis Code 1 Diagnosis Present on Admission (POA) Indicator Code	Char	1	63
CLM_POA_IND_SW2	Claim Diagnosis Code 2 Diagnosis Present on Admission (POA) Indicator Code	Char	1	64
CLM_POA_IND_SW3	Claim Diagnosis Code 3 Diagnosis Present on Admission (POA) Indicator Code	Char	1	65
CLM_POA_IND_SW4	Claim Diagnosis Code 4 Diagnosis Present on Admission (POA) Indicator Code	Char	1	66
CLM_POA_IND_SW5	Claim Diagnosis Code 5 Diagnosis Present on Admission (POA) Indicator Code	Char	1	67
CLM_POA_IND_SW6	Claim Diagnosis Code 6 Diagnosis Present on Admission (POA) Indicator Code	Char	1	68
CLM_POA_IND_SW7	Claim Diagnosis Code 7 Diagnosis Present on Admission (POA) Indicator Code	Char	1	69
CLM_POA_IND_SW8	Claim Diagnosis Code 8 Diagnosis Present on Admission (POA) Indicator Code	Char	1	70
CLM_POA_IND_SW9	Claim Diagnosis Code 9 Diagnosis Present on Admission (POA) Indicator Code	Char	1	71
CLM_POA_IND_SW10	Claim Diagnosis Code 10 Diagnosis Present on Admission (POA) Indicator Code	Char	1	72

CLM_POA_IND_SW11	Claim Diagnosis Code 11 Diagnosis Present on Admission (POA) Indicator Code	Char	1	73
CLM_POA_IND_SW12	Claim Diagnosis Code 12 Diagnosis Present on Admission (POA) Indicator Code	Char	1	74
CLM_POA_IND_SW13	Claim Diagnosis Code 13 Diagnosis Present on Admission (POA) Indicator Code	Char	1	75
CLM_POA_IND_SW14	Claim Diagnosis Code 14 Diagnosis Present on Admission (POA) Indicator Code	Char	1	76
CLM_POA_IND_SW15	Claim Diagnosis Code 15 Diagnosis Present on Admission (POA) Indicator Code	Char	1	77
CLM_POA_IND_SW16	Claim Diagnosis Code 16 Diagnosis Present on Admission (POA) Indicator Code	Char	1	78
CLM_POA_IND_SW17	Claim Diagnosis Code 17 Diagnosis Present on Admission (POA) Indicator Code	Char	1	79
CLM_POA_IND_SW18	Claim Diagnosis Code 18 Diagnosis Present on Admission (POA) Indicator Code	Char	1	80
CLM_POA_IND_SW19	Claim Diagnosis Code 19 Diagnosis Present on Admission (POA) Indicator Code	Char	1	81
CLM_POA_IND_SW20	Claim Diagnosis Code 20 Diagnosis Present on Admission (POA) Indicator Code	Char	1	82
CLM_POA_IND_SW21	Claim Diagnosis Code 21 Diagnosis Present on Admission (POA) Indicator Code	Char	1	83
CLM_POA_IND_SW22	Claim Diagnosis Code 22 Diagnosis Present on Admission (POA) Indicator Code	Char	1	84
CLM_POA_IND_SW23	Claim Diagnosis Code 23 Diagnosis Present on Admission (POA) Indicator Code	Char	1	85
CLM_POA_IND_SW24	Claim Diagnosis Code 24 Diagnosis Present on Admission (POA) Indicator Code	Char	1	86
CLM_POA_IND_SW25	Claim Diagnosis Code 25 Diagnosis Present on Admission (POA) Indicator Code	Char	1	87
CLM_1ST_DGNS_E_CD	First Claim Diagnosis E Code	Char	7	88
ICD_DGNS_E_CD1	Claim Diagnosis E Code 1	Char	7	89
ICD_DGNS_E_CD2	Claim Diagnosis E Code 2	Char	7	90
ICD_DGNS_E_CD3	Claim Diagnosis E Code 3	Char	7	91
ICD_DGNS_E_CD4	Claim Diagnosis E Code 4	Char	7	92
ICD_DGNS_E_CD5	Claim Diagnosis E Code 5	Char	7	93
ICD_DGNS_E_CD6	Claim Diagnosis E Code 6	Char	7	94
ICD_DGNS_E_CD7	Claim Diagnosis E Code 7	Char	7	95
ICD_DGNS_E_CD8	Claim Diagnosis E Code 8	Char	7	96
ICD_DGNS_E_CD9	Claim Diagnosis E Code 9	Char	7	97

ICD_DGNS_E_CD10	Claim Diagnosis E Code 10	Char	7	98
CLM_E_POA_IND_SW1	Claim Diagnosis E Code 1 Diagnosis Present on Admission Indicator Code	Char	1	99
CLM_E_POA_IND_SW2	Claim Diagnosis E Code 2 Diagnosis Present on Admission Indicator Code	Char	1	100
CLM_E_POA_IND_SW3	Claim Diagnosis E Code 3 Diagnosis Present on Admission Indicator Code	Char	1	101
CLM_E_POA_IND_SW4	Claim Diagnosis E Code 4 Diagnosis Present on Admission Indicator Code	Char	1	102
CLM_E_POA_IND_SW5	Claim Diagnosis E Code 5 Diagnosis Present on Admission Indicator Code	Char	1	103
CLM_E_POA_IND_SW6	Claim Diagnosis E Code 6 Diagnosis Present on Admission Indicator Code	Char	1	104
CLM_E_POA_IND_SW7	Claim Diagnosis E Code 7 Diagnosis Present on Admission Indicator Code	Char	1	105
CLM_E_POA_IND_SW8	Claim Diagnosis E Code 8 Diagnosis Present on Admission Indicator Code	Char	1	106
CLM_E_POA_IND_SW9	Claim Diagnosis E Code 9 Diagnosis Present on Admission Indicator Code	Char	1	107
CLM_E_POA_IND_SW10	Claim Diagnosis E Code 10 Diagnosis Present on Admission Indicator Code	Char	1	108
ICD_PRCDR_CD1	Claim Procedure Code 1	Char	7	109
ICD_PRCDR_CD2	Claim Procedure Code 2	Char	7	110
ICD_PRCDR_CD3	Claim Procedure Code 3	Char	7	111
ICD_PRCDR_CD4	Claim Procedure Code 4	Char	7	112
ICD_PRCDR_CD5	Claim Procedure Code 5	Char	7	113
ICD_PRCDR_CD6	Claim Procedure Code 6	Char	7	114
ICD_PRCDR_CD7	Claim Procedure Code 7	Char	7	115
ICD_PRCDR_CD8	Claim Procedure Code 8	Char	7	116
ICD_PRCDR_CD9	Claim Procedure Code 9	Char	7	117
ICD_PRCDR_CD10	Claim Procedure Code 10	Char	7	118
ICD_PRCDR_CD11	Claim Procedure Code 11	Char	7	119
ICD_PRCDR_CD12	Claim Procedure Code 12	Char	7	120
ICD_PRCDR_CD13	Claim Procedure Code 13	Char	7	121
PRCDR_DT1	Claim Procedure Code 1 Date	Date	8	122
PRCDR_DT2	Claim Procedure Code 2 Date	Date	8	123
PRCDR_DT3	Claim Procedure Code 3 Date	Date	8	124
PRCDR_DT4	Claim Procedure Code 4 Date	Date	8	125
PRCDR_DT5	Claim Procedure Code 5 Date	Date	8	126
PRCDR_DT6	Claim Procedure Code 6 Date	Date	8	127
PRCDR_DT7	Claim Procedure Code 7 Date	Date	8	128
PRCDR_DT8	Claim Procedure Code 8 Date	Date	8	129
PRCDR_DT9	Claim Procedure Code 9 Date	Date	8	130
PRCDR_DT10	Claim Procedure Code 10 Date	Date	8	131
PRCDR_DT11	Claim Procedure Code 11 Date	Date	8	132
PRCDR_DT12	Claim Procedure Code 12 Date	Date	8	133
PRCDR_DT13	Claim Procedure Code 13 Date	Date	8	134
CLM_OBSLT_DT	Claim Obsolete Date	Date	8	135
CLM_BPRVDR_CITY_NAME	Billing Provider Address - City	Char	30	136
CLM_BPRVDR_USPS_STATE_CD	Billing Provider Address - USPS State	Char	2	137

	Code			
CLM_BPRVDR_ADR_ZIP_CD	Billing Provider Address - ZIP Code	Char	9	138
CLM_SUBSCR_CITY_NAME	Medicare Subscriber Address - City	Char	30	139
CLM_SUBSCR_USPS_STATE_CD	Medicare Subscriber Address - USPS State Code	Char	2	140
CLM_SUBSCR_ADR_ZIP_CD	Medicare Subscriber Address - ZIP Code	Char	9	141
BENE_CNTY_CD	Beneficiary County Code from Claim (SSA)	Char	3	142
BENE_STATE_CD	Beneficiary Residence (SSA) State Code	Char	2	143
BENE_MLG_CNTCT_ZIP_CD	Beneficiary ZIP Code of Residence	Char	9	144
GNDR_CD	Gender Code	Char	1	145
BENE_RACE_CD	Race Code	Char	1	146
DOB_DT	Date of Birth	Date	8	147
BENE_MDCR_STUS_CD	Beneficiary Medicare Status Code	Char	2	148
TAX_NUM	Provider Tax Number	Char	10	149
BENE_STATE	Beneficiary State Postal Code	Char	2	150

Revenue Center File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
CLM_LINE_NUM	Claim Line Number	Num	13	4
LINE_NUM_ORIG	Original Claim Line Number	Num	13	19
CLM_THRU_DT	Claim Through Date	Date	8	5
REV_CNTR	Revenue Center Code	Char	4	6
REV_CNTR_FROM_DT	Revenue Center From Date	Date	8	7
REV_CNTR_THRU_DT	Revenue Center Thru Date	Date	8	8
REV_CNTR_UNIT_CNT	Revenue Center Unit Count	Num	8	9
HCPCS_CD	HCFA Common Procedure Coding System (HCPCS) Code	Char	5	10
HCPCS_1ST_MDFR_CD	HCPCS Initial Modifier Code	Char	2	11
HCPCS_2ND_MDFR_CD	HCPCS Second Modifier Code	Char	2	12
HCPCS_3RD_MDFR_CD	HCPCS Third Modifier Code	Char	2	13
REV_CNTR_IDE_NDC_UPC_NUM	Revenue Center IDE, NDC, or UPC Number	Char	24	14
REV_CNTR_NDC_QTY	Revenue Center National Drug Code (NDC) Quantity	Num	10	15
REV_CNTR_NDC_QTY_QLFR_CD	Revenue Center NDC Quantity Qualifier Code	Char	2	16
REV_CNTR_RNDRNG_PHYSN_NPI	Revenue Center Rendering Physician NPI	Char	10	17
LINE_LTST_CLM_IND	Line Latest Claim Indicator	Char	1	18

Condition Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_COND_CD_SEQ	Claim Related Condition Code Sequence	Char	2	4
CLM_RLT_COND_CD	Claim Related Condition Code	Char	2	5

Occurrence Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1

ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_OCRNC_CD_SEQ	Claim Related Occurrence Code Sequence	Char	2	4
CLM_RLT_OCRNC_CD	Claim Related Occurrence Code	Char	2	5
CLM_RLT_OCRNC_DT	Claim Related Occurrence Date	Date	8	6

Span Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_SPAN_CD_SEQ	Claim Related Span Code Sequence	Char	2	4
CLM_SPAN_CD	Claim Occurrence Span Code	Char	2	5
CLM_SPAN_FROM_DT	Claim Occurrence Span From Date	Date	8	6
CLM_SPAN_THRU_DT	Claim Occurrence Span Through Date	Date	8	7

Value Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_VAL_CD_SEQ	Claim Related Value Code Sequence	Char	2	4
CLM_VAL_CD	Claim Value Code	Char	2	5

Appendix D: Hospital Outpatient Services Variables and Names

SAS Name	Label	Type	Length	2015
Base Claim File				
BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
SAMPLE_GROUP	CCW Beneficiary Random Sample Group	Char	2	2
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	3
CLM_TYPE_CD	Claim Type Code	Char	4	4
CLM_FROM_DT	Claim From Date	Date	8	5
CLM_THRU_DT	Claim Through Date	Date	8	6
SRVC_MONTH	Service Month	Date	6	7
CLM_CHRT_RVW_SW	Claim Chart Review Switch	Char	1	8
CLM_CNTL_NUM	Claim Control Number	Char	23	9
CLM_ORIG_CNTL_NUM	Claim Original Control Number	Char	23	10
• CLM_FINL_ACTN_IND	Claim Final Action Indicator	Char	1	11
• CLM_LTST_CLM_IND	Latest Claim Indicator	Char	1	12
EDPS_CREATE_DT	Encounter Data Processing System (EDPS) Create Date	Date	8	13
CLM_RCPT_DT	Claim Receipt Date	Date	8	14
CLM_FAC_TYPE_CD	Claim Facility Type Code	Char	1	15
CLM_SRVC_CLSFCTN_TYPE_CD	Claim Service classification Type Code	Char	1	16
CLM_FREQ_CD	Claim Frequency Code	Char	1	17
CNTRCT_NUM	Medicare Part C Contract Number	Char	5	18
CNTRCT_PBP_NUM	Medicare Part C Plan Benefit Package (PBP) Number	Char	3	19
CLM_MDCL_REC	Claim Medical Record Number	Char	1	20
ORG_NPI	Organization NPI Number	Char	10	21
ORG_TXNMY_CD	Organization Taxonomy Code	Char	10	22
RNDRNG_PHYSN_NPI	Claim Rendering Physician NPI Number	Char	10	23
RFRG_PHYSN_NPI	Claim Referring Physician NPI Number	Char	10	24
AT_PHYSN_NPI	Claim Attending Physician NPI Number	Char	10	25
AT_PHSYN_TXNMY_CD	Claim Attending Physician Taxonomy Code	Char	10	26
OP_PHYSN_NPI	Claim Operating Physician NPI Number	Char	10	27
OT_PHYSN_NPI	Claim Other Physician NPI Number	Char	10	28
PTNT_DSCHRG_STUS_CD	Patient Discharge Status Code	Char	2	29
PRNCPAL_DGNS_CD	Claim Principal Diagnosis Code	Char	7	30
ICD_DGNS_CD1	Claim Diagnosis Code 1	Char	7	31
ICD_DGNS_CD2	Claim Diagnosis Code 2	Char	7	32
ICD_DGNS_CD3	Claim Diagnosis Code 3	Char	7	33
ICD_DGNS_CD4	Claim Diagnosis Code 4	Char	7	34
ICD_DGNS_CD5	Claim Diagnosis Code 5	Char	7	35
ICD_DGNS_CD6	Claim Diagnosis Code 6	Char	7	36
ICD_DGNS_CD7	Claim Diagnosis Code 7	Char	7	37
ICD_DGNS_CD8	Claim Diagnosis Code 8	Char	7	38
ICD_DGNS_CD9	Claim Diagnosis Code 9	Char	7	39
ICD_DGNS_CD10	Claim Diagnosis Code 10	Char	7	40
ICD_DGNS_CD11	Claim Diagnosis Code 11	Char	7	41
ICD_DGNS_CD12	Claim Diagnosis Code 12	Char	7	42

ICD_DGNS_CD13	Claim Diagnosis Code 13	Char	7	43
ICD_DGNS_CD14	Claim Diagnosis Code 14	Char	7	44
ICD_DGNS_CD15	Claim Diagnosis Code 15	Char	7	45
ICD_DGNS_CD16	Claim Diagnosis Code 16	Char	7	46
ICD_DGNS_CD17	Claim Diagnosis Code 17	Char	7	47
ICD_DGNS_CD18	Claim Diagnosis Code 18	Char	7	48
ICD_DGNS_CD19	Claim Diagnosis Code 19	Char	7	49
ICD_DGNS_CD20	Claim Diagnosis Code 20	Char	7	50
ICD_DGNS_CD21	Claim Diagnosis Code 21	Char	7	51
ICD_DGNS_CD22	Claim Diagnosis Code 22	Char	7	52
ICD_DGNS_CD23	Claim Diagnosis Code 23	Char	7	53
ICD_DGNS_CD24	Claim Diagnosis Code 24	Char	7	54
ICD_DGNS_CD25	Claim Diagnosis Code 25	Char	7	55
CLM_1ST_DGNS_E_CD	First Claim Diagnosis E Code	Char	7	56
ICD_DGNS_E_CD1	Claim Diagnosis E Code 1	Char	7	57
ICD_DGNS_E_CD2	Claim Diagnosis E Code 2	Char	7	58
ICD_DGNS_E_CD3	Claim Diagnosis E Code 3	Char	7	59
ICD_DGNS_E_CD4	Claim Diagnosis E Code 4	Char	7	60
ICD_DGNS_E_CD5	Claim Diagnosis E Code 5	Char	7	61
ICD_DGNS_E_CD6	Claim Diagnosis E Code 6	Char	7	62
ICD_DGNS_E_CD7	Claim Diagnosis E Code 7	Char	7	63
ICD_DGNS_E_CD8	Claim Diagnosis E Code 8	Char	7	64
ICD_DGNS_E_CD9	Claim Diagnosis E Code 9	Char	7	65
ICD_DGNS_E_CD10	Claim Diagnosis E Code 10	Char	7	66
RSN_VISIT_CD1	Reason for Visit Diagnosis Code 1	Char	7	67
RSN_VISIT_CD2	Reason for Visit Diagnosis Code 2	Char	7	68
RSN_VISIT_CD3	Reason for Visit Diagnosis Code 3	Char	7	69
ICD_PRCDR_CD1	Claim Procedure Code 1	Char	7	70
ICD_PRCDR_CD2	Claim Procedure Code 2	Char	7	71
ICD_PRCDR_CD3	Claim Procedure Code 3	Char	7	72
ICD_PRCDR_CD4	Claim Procedure Code 4	Char	7	73
ICD_PRCDR_CD5	Claim Procedure Code 5	Char	7	74
ICD_PRCDR_CD6	Claim Procedure Code 6	Char	7	75
ICD_PRCDR_CD7	Claim Procedure Code 7	Char	7	76
ICD_PRCDR_CD8	Claim Procedure Code 8	Char	7	77
ICD_PRCDR_CD9	Claim Procedure Code 9	Char	7	78
ICD_PRCDR_CD10	Claim Procedure Code 10	Char	7	79
ICD_PRCDR_CD11	Claim Procedure Code 11	Char	7	80
ICD_PRCDR_CD12	Claim Procedure Code 12	Char	7	81
ICD_PRCDR_CD13	Claim Procedure Code 13	Char	7	82
PRCDR_DT1	Claim Procedure Code 1 Date	Date	8	83
PRCDR_DT2	Claim Procedure Code 2 Date	Date	8	84
PRCDR_DT3	Claim Procedure Code 3 Date	Date	8	85
PRCDR_DT4	Claim Procedure Code 4 Date	Date	8	86
PRCDR_DT5	Claim Procedure Code 5 Date	Date	8	87
PRCDR_DT6	Claim Procedure Code 6 Date	Date	8	88
PRCDR_DT7	Claim Procedure Code 7 Date	Date	8	89
PRCDR_DT8	Claim Procedure Code 8 Date	Date	8	90
PRCDR_DT9	Claim Procedure Code 9 Date	Date	8	91
PRCDR_DT10	Claim Procedure Code 10 Date	Date	8	92

PRCDR_DT11	Claim Procedure Code 11 Date	Date	8	93
PRCDR_DT12	Claim Procedure Code 12 Date	Date	8	94
PRCDR_DT13	Claim Procedure Code 13 Date	Date	8	95
CLM_OBSLT_DT	Claim Obsolete Date	Date	8	96
CLM_BPRVDR_CITY_NAME	Billing Provider Address - City	Char	30	97
CLM_BPRVDR_USPS_STATE_CD	Billing Provider Address - USPS State Code	Char	2	98
CLM_BPRVDR_ADR_ZIP_CD	Billing Provider Address - ZIP Code	Char	9	99
CLM_SUBSCR_CITY_NAME	Medicare Subscriber Address - City	Char	30	100
CLM_SUBSCR_USPS_STATE_CD	Medicare Subscriber Address - USPS State Code	Char	2	101
CLM_SUBSCR_ADR_ZIP_CD	Medicare Subscriber Address - ZIP Code	Char	9	102
BENE_CNTY_CD	Beneficiary County Code from Claim (SSA)	Char	3	103
BENE_STATE_CD	Beneficiary Residence (SSA) State Code	Char	2	104
BENE_MLG_CNTCT_ZIP_CD	Beneficiary ZIP Code of Residence	Char	9	105
GNDR_CD	Gender Code	Char	1	106
BENE_RACE_CD	Race Code	Char	1	107
DOB_DT	Date of Birth	Date	8	108
BENE_MDCR_STUS_CD	Beneficiary Medicare Status Code	Char	2	109
TAX_NUM	Provider Tax Number	Char	10	110
BENE_STATE	Beneficiary State Postal Code	Char	2	111
Revenue Center File				
BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
CLM_LINE_NUM	Claim Line Number	Num	13	4
LINE_NUM_ORIG	Original Claim Line Number	Num	13	20
CLM_THRU_DT	Claim Through Date	Date	8	5
REV_CNTR	Revenue Center Code	Char	4	6
REV_CNTR_FROM_DT	Revenue Center From Date	Date	8	7
REV_CNTR_THRU_DT	Revenue Center Thru Date	Date	8	8
REV_CNTR_UNIT_CNT	Revenue Center Unit Count	Num	8	9
HCPCS_CD	HCFA Common Procedure Coding System (HCPCS) Code	Char	5	10
HCPCS_1ST_MDFR_CD	HCPCS Initial Modifier Code	Char	2	11
HCPCS_2ND_MDFR_CD	HCPCS Second Modifier Code	Char	2	12
HCPCS_3RD_MDFR_CD	HCPCS Third Modifier Code	Char	2	13
HCPCS_4TH_MDFR_CD	HCPCS Fourth Modifier Code	Char	2	14
REV_CNTR_IDE_NDC_UPC_NUM	Revenue Center IDE, NDC, or UPC Number	Char	24	15
REV_CNTR_NDC_QTY	Revenue Center National Drug Code (NDC) Quantity	Num	10	16
REV_CNTR_NDC_QTY_QLFR_CD	Revenue Center NDC Quantity Qualifier Code	Char	2	17
REV_CNTR_RNDRNG_PHYSN_NPI	Revenue Center Rendering Physician NPI	Char	10	18
LINE_LTST_CLM_IND	Line Latest Claim Indicator	Char	1	19
Condition Code File				
BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2

CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_COND_CD_SEQ	Claim Related Condition Code Sequence	Char	2	4
CLM_RLT_COND_CD	Claim Related Condition Code	Char	2	5

Occurrence Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_OCRNC_CD_SEQ	Claim Related Occurrence Code Sequence	Char	2	4
CLM_RLT_OCRNC_CD	Claim Related Occurrence Code	Char	2	5
CLM_RLT_OCRNC_DT	Claim Related Occurrence Date	Date	8	6

Span Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_SPAN_CD_SEQ	Claim Related Span Code Sequence	Char	2	4
CLM_SPAN_CD	Claim Occurrence Span Code	Char	2	5
CLM_SPAN_FROM_DT	Claim Occurrence Span From Date	Date	8	6
CLM_SPAN_THRU_DT	Claim Occurrence Span Through Date	Date	8	7

Value Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_VAL_CD_SEQ	Claim Related Value Code Sequence	Char	2	4
CLM_VAL_CD	Claim Value Code	Char	2	5

Appendix E: Home Health Variables and Names

SAS Name	Label	Type	Length	2015
Base Claim File				
BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
SAMPLE_GROUP	CCW Beneficiary Random Sample Group	Char	2	2
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	3
CLM_TYPE_CD	Claim Type Code	Char	4	4
CLM_FROM_DT	Claim From Date	Date	8	5
CLM_THRU_DT	Claim Through Date	Date	8	6
SRVC_MONTH	Service Month	Date	6	7
CLM_CHRT_RVW_SW	Claim Chart Review Switch	Char	1	8
CLM_CNTL_NUM	Claim Control Number	Char	23	9
CLM_ORIG_CNTL_NUM	Claim Original Control Number	Char	23	10
CLM_FINL_ACTN_IND	Claim Final Action Indicator	Char	1	11
CLM_LTST_CLM_IND	Latest Claim Indicator	Char	1	12
EDPS_CREATE_DT	Encounter Data Processing System (EDPS) Create Date	Date	8	13
CLM_RCPT_DT	Claim Receipt Date	Date	8	14
CLM_FAC_TYPE_CD	Claim Facility Type Code	Char	1	15
CLM_SRVC_CLSFCTN_TYPE_CD	Claim Service classification Type Code	Char	1	16
CLM_FREQ_CD	Claim Frequency Code	Char	1	17
CNTRCT_NUM	Medicare Part C Contract Number	Char	5	18
CNTRCT_PBP_NUM	Medicare Part C Plan Benefit Package (PBP) Number	Char	3	19
CLM_MDCL_REC	Claim Medical Record Number	Char	1	20
ORG_NPI	Organization NPI Number	Char	10	21
ORG_TXNMY_CD	Organization Taxonomy Code	Char	10	22
RNDRNG_PHYSN_NPI	Claim Rendering Physician NPI Number	Char	10	23
RFRG_PHYSN_NPI	Claim Referring Physician NPI Number	Char	10	24
AT_PHYSN_NPI	Claim Attending Physician NPI Number	Char	10	25
AT_PHYSN_TXNMY_CD	Claim Attending Physician Taxonomy Code	Char	10	26
OP_PHYSN_NPI	Claim Operating Physician NPI Number	Char	10	27
OT_PHYSN_NPI	Claim Other Physician NPI Number	Char	10	28
CLM_ADMSN_DT	Claim Admission Date	Date	8	29
PTNT_DSCHRG_STUS_CD	Patient Discharge Status Code	Char	2	30
BENE_DSCHRG_DT	Beneficiary Discharge Date	Date	8	31
PRNCPAL_DGNS_CD	Claim Principal Diagnosis Code	Char	7	32
ICD_DGNS_CD1	Claim Diagnosis Code 1	Char	7	33
ICD_DGNS_CD2	Claim Diagnosis Code 2	Char	7	34
ICD_DGNS_CD3	Claim Diagnosis Code 3	Char	7	35
ICD_DGNS_CD4	Claim Diagnosis Code 4	Char	7	36
ICD_DGNS_CD5	Claim Diagnosis Code 5	Char	7	37
ICD_DGNS_CD6	Claim Diagnosis Code 6	Char	7	38
ICD_DGNS_CD7	Claim Diagnosis Code 7	Char	7	39

ICD_DGNS_CD8	Claim Diagnosis Code 8	Char	7	40
ICD_DGNS_CD9	Claim Diagnosis Code 9	Char	7	41
ICD_DGNS_CD10	Claim Diagnosis Code 10	Char	7	42
ICD_DGNS_CD11	Claim Diagnosis Code 11	Char	7	43
ICD_DGNS_CD12	Claim Diagnosis Code 12	Char	7	44
ICD_DGNS_CD13	Claim Diagnosis Code 13	Char	7	45
ICD_DGNS_CD14	Claim Diagnosis Code 14	Char	7	46
ICD_DGNS_CD15	Claim Diagnosis Code 15	Char	7	47
ICD_DGNS_CD16	Claim Diagnosis Code 16	Char	7	48
ICD_DGNS_CD17	Claim Diagnosis Code 17	Char	7	49
ICD_DGNS_CD18	Claim Diagnosis Code 18	Char	7	50
ICD_DGNS_CD19	Claim Diagnosis Code 19	Char	7	51
ICD_DGNS_CD20	Claim Diagnosis Code 20	Char	7	52
ICD_DGNS_CD21	Claim Diagnosis Code 21	Char	7	53
ICD_DGNS_CD22	Claim Diagnosis Code 22	Char	7	54
ICD_DGNS_CD23	Claim Diagnosis Code 23	Char	7	55
ICD_DGNS_CD24	Claim Diagnosis Code 24	Char	7	56
ICD_DGNS_CD25	Claim Diagnosis Code 25	Char	7	57
CLM_1ST_DGNS_E_CD	First Claim Diagnosis E Code	Char	7	58
ICD_DGNS_E_CD1	Claim Diagnosis E Code 1	Char	7	59
ICD_DGNS_E_CD2	Claim Diagnosis E Code 2	Char	7	60
ICD_DGNS_E_CD3	Claim Diagnosis E Code 3	Char	7	61
RSN_VISIT_CD1	Reason for Visit Diagnosis Code 1	Char	7	62
RSN_VISIT_CD2	Reason for Visit Diagnosis Code 2	Char	7	63
RSN_VISIT_CD3	Reason for Visit Diagnosis Code 3	Char	7	64
CLM_OBSLT_DT	Claim Obsolete Date	Date	8	65
CLM_BPRVDR_CITY_NAME	Billing Provider Address - City	Char	30	66
CLM_BPRVDR_USPS_STATE_CD	Billing Provider Address - USPS State Code	Char	2	67
CLM_BPRVDR_ADR_ZIP_CD	Billing Provider Address - ZIP Code	Char	9	68
CLM_SUBSCR_CITY_NAME	Medicare Subscriber Address - City	Char	30	69
CLM_SUBSCR_USPS_STATE_CD	Medicare Subscriber Address - USPS State Code	Char	2	70
CLM_SUBSCR_ADR_ZIP_CD	Medicare Subscriber Address - ZIP Code	Char	9	71
BENE_CNTY_CD	Beneficiary County Code from Claim (SSA)	Char	3	72
BENE_STATE_CD	Beneficiary Residence (SSA) State Code	Char	2	73
BENE_MLG_CNTCT_ZIP_CD	Beneficiary ZIP Code of Residence	Char	9	74
GNDR_CD	Gender Code	Char	1	75
BENE_RACE_CD	Race Code	Char	1	76
DOB_DT	Date of Birth	Date	8	77
BENE_MDCR_STUS_CD	Beneficiary Medicare Status Code	Char	2	78
TAX_NUM	Provider Tax Number	Char	10	79
BENE_STATE	Beneficiary State Postal Code	Char	2	80

Revenue Center File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3

CLM_LINE_NUM	Claim Line Number	Num	13	4
LINE_NUM_ORIG	Original Claim Line Number	Num	13	19
CLM_THRU_DT	Claim Through Date	Date	8	5
REV_CNTR	Revenue Center Code	Char	4	6
REV_CNTR_FROM_DT	Revenue Center From Date	Date	8	7
REV_CNTR_THRU_DT	Revenue Center Thru Date	Date	8	8
REV_CNTR_UNIT_CNT	Revenue Center Unit Count	Num	8	9
HCPCS_CD	HCFA Common Procedure Coding System (HCPCS) Code	Char	5	10
HCPCS_1ST_MDFR_CD	HCPCS Initial Modifier Code	Char	2	11
HCPCS_2ND_MDFR_CD	HCPCS Second Modifier Code	Char	2	12
HCPCS_3RD_MDRF_CD	HCPCS Third Modifier Code	Char	2	13
REV_CNTR_IDE_NDC_UPC_NUM	Revenue Center IDE, NDC, or UPC Number	Char	24	14
REV_CNTR_NDC_QTY	Revenue Center National Drug Code (NDC) Quantity	Num	10	15
REV_CNTR_NDC_QTY_QLFR_CD	Revenue Center NDC Quantity Qualifier Code	Char	2	16
REV_CNTR_RNDRNG_PHYSN_NPI	Revenue Center Rendering Physician NPI	Char	10	17
LINE_LTST_CLM_IND	Line Latest Claim Indicator	Char	1	18

Condition Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_COND_CD_SEQ	Claim Related Condition Code Sequence	Char	2	4
CLM_RLT_COND_CD	Claim Related Condition Code	Char	2	5

Occurrence Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_OCRNC_CD_SEQ	Claim Related Occurrence Code Sequence	Char	2	4
CLM_RLT_OCRNC_CD	Claim Related Occurrence Code	Char	2	5
CLM_RLT_OCRNC_DT	Claim Related Occurrence Date	Date	8	6

Span Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
RLT_SPAN_CD_SEQ	Claim Related Span Code Sequence	Char	2	4
CLM_SPAN_CD	Claim Occurrence Span Code	Char	2	5
CLM_SPAN_FROM_DT	Claim Occurrence Span From Date	Date	8	6
CLM_SPAN_THRU_DT	Claim Occurrence Span Through Date	Date	8	7

Value Code File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3

RLT_VAL_CD_SEQ	Claim Related Value Code Sequence	Char	2	4
CLM_VAL_CD	Claim Value Code	Char	2	5

Appendix F: Carrier Variables and Names

SAS Name	Label	Type	Length	2015
Base Claim File				
BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
SAMPLE_GROUP	CCW Beneficiary Random Sample Group	Char	2	2
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	3
CLM_TYPE_CD	Claim Type Code	Char	4	4
CLM_FROM_DT	Claim From Date	Date	8	5
CLM_THRU_DT	Claim Through Date	Date	8	6
SRVC_MONTH	Service Month	Date	6	7
CLM_CHRT_RVW_SW	Claim Chart Review Switch	Char	1	8
CLM_CNTL_NUM	Claim Control Number	Char	23	9
CLM_ORIG_CNTL_NUM	Claim Original Control Number	Char	23	10
CLM_FINL_ACTN_IND	Claim Final Action Indicator	Char	1	11
CLM_LTST_CLM_IND	Latest Claim Indicator	Char	1	12
EDPS_CREATE_DT	Encounter Data Processing System (EDPS) Create Date	Date	8	13
CLM_RCPT_DT	Claim Receipt Date	Date	8	14
CLM_FREQ_CD	Claim Frequency Code	Char	1	15
CNTRCT_NUM	Medicare Part C Contract Number	Char	5	16
CNTRCT_PBP_NUM	Medicare Part C Plan Benefit Package (PBP) Number	Char	3	17
CLM_MDCL_REC	Claim Medical Record Number	Char	1	18
ORG_NPI	Organization NPI Number	Char	10	19
ORG_TXNMY_CD	Organization Taxonomy Code	Char	10	20
RFRG_PHYSN_NPI	Claim Referring Physician NPI Number	Char	10	21
PRNCPAL_DGNS_CD	Claim Principal Diagnosis Code	Char	7	22
PRNCPAL_DGNS_VRSN_CD	Claim Principal Diagnosis Version Code	Char	1	23
ICD_DGNS_CD1	Claim Diagnosis Code 1	Char	7	24
ICD_DGNS_VRSN_CD1	Claim Diagnosis Code I Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	25
ICD_DGNS_CD2	Claim Diagnosis Code 2	Char	7	26
ICD_DGNS_VRSN_CD2	Claim Diagnosis Code II Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	27
ICD_DGNS_CD3	Claim Diagnosis Code 3	Char	7	28
ICD_DGNS_VRSN_CD3	Claim Diagnosis Code III Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	29
ICD_DGNS_CD4	Claim Diagnosis Code 4	Char	7	30
ICD_DGNS_VRSN_CD4	Claim Diagnosis Code IV Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	31
ICD_DGNS_CD5	Claim Diagnosis Code 5	Char	7	32
ICD_DGNS_VRSN_CD5	Claim Diagnosis Code V Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	33
ICD_DGNS_CD6	Claim Diagnosis Code 6	Char	7	34
ICD_DGNS_VRSN_CD6	Claim Diagnosis Code VI Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	35
ICD_DGNS_CD7	Claim Diagnosis Code 7	Char	7	36
ICD_DGNS_VRSN_CD7	Claim Diagnosis Code VII Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	37

ICD_DGNS_CD8	Claim Diagnosis Code 8	Char	7	38
ICD_DGNS_VRSN_CD8	Claim Diagnosis Code VIII Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	39
ICD_DGNS_CD9	Claim Diagnosis Code 9	Char	7	40
ICD_DGNS_VRSN_CD9	Claim Diagnosis Code IX Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	41
ICD_DGNS_CD10	Claim Diagnosis Code 10	Char	7	42
ICD_DGNS_VRSN_CD10	Claim Diagnosis Code X Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	43
ICD_DGNS_CD11	Claim Diagnosis Code 11	Char	7	44
ICD_DGNS_VRSN_CD11	Claim Diagnosis Code XI Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	45
ICD_DGNS_CD12	Claim Diagnosis Code 12	Char	7	46
ICD_DGNS_VRSN_CD12	Claim Diagnosis Code XII Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	47
ICD_DGNS_CD13	Claim Diagnosis Code 13	Char	7	48
ICD_DGNS_VRSN_CD13	Claim Diagnosis Code XIII Diagnosis Version Code (ICD-9 or ICD-10)	Char	1	49
CLM_OBSLT_DT	Claim Obsolete Date	Date	8	50
CLM_BPRVDR_CITY_NAME	Billing Provider Address - City	Char	30	51
CLM_BPRVDR_USPS_STATE_CD	Billing Provider Address - USPS State Code	Char	2	52
CLM_BPRVDR_ADR_ZIP_CD	Billing Provider Address - ZIP Code	Char	9	53
CLM_SUBSCR_CITY_NAME	Medicare Subscriber Address - City	Char	30	54
CLM_SUBSCR_USPS_STATE_CD	Medicare Subscriber Address - USPS State Code	Char	2	55
CLM_SUBSCR_ADR_ZIP_CD	Medicare Subscriber Address - ZIP Code	Char	9	56
BENE_CNTY_CD	Beneficiary County Code from Claim (SSA)	Char	3	57
BENE_STATE_CD	Beneficiary Residence (SSA) State Code	Char	2	58
BENE_MLG_CNTCT_ZIP_CD	Beneficiary ZIP Code of Residence	Char	9	59
GNDR_CD	Gender Code	Char	1	60
BENE_RACE_CD	Race Code	Char	1	61
DOB_DT	Date of Birth	Date	8	62
BENE_MDCR_STUS_CD	Beneficiary Medicare Status Code	Char	2	63
TAX_NUM	Provider Tax Number	Char	10	64
BENE_STATE	Beneficiary State Postal Code	Char	2	65

Line File

BENE_ID	Encrypted CCW Beneficiary ID	Char	15	1
ENC_JOIN_KEY	Unique Encounter Join Key	Char	15	2
CLM_TYPE_CD	Claim Type Code	Char	4	3
CLM_LINE_NUM	Claim Line Number	Num	13	4
LINE_NUM_ORIG	Original Claim Line Number	Num	13	20
CLM_THRU_DT	Claim Through Date	Date	8	5
PRVDR_NPI	Line Rendering Physician NPI	Char	10	6
PRVDR_SPCLTY	Line CMS Provider Specialty Code	Char	2	7
LINE_SRVC_CNT	Line Service Count	Num	12	8
LINE_PLACE_OF_SRVC_CD	Line Place of Service Code	Char	2	9
LINE_1ST_EXPNS_DT	Line First Expense Date	Date	8	10
LINE_LAST_EXPNS_DT	Line Last Expense Date	Date	8	11
HCPCS_CD	HCFA Common Procedure Coding System	Char	5	12

	(HCPCS) Code			
HCPCS_1ST_MDFR_CD	HCPCS Initial Modifier Code	Char	2	13
HCPCS_2ND_MDFR_CD	HCPCS Second Modifier Code	Char	2	14
HCPCS_3RD_MDFR_CD	HCPCS Third Modifier Code	Char	2	15
HCPCS_4TH_MDFR_CD	HCPCS Fourth Modifier Code	Char	2	16
LINE_NDC_CD	Line National Drug Code (NDC)	Char	11	17
LINE_RX_NUM	Line RX Number	Char	30	18
LINE_LTST_CLM_IND	Line Latest Claim Indicator	Char	1	19

Appendix G: Provider Variables and Names

Variable Name	Description	Data Source
ID variables		
npi	National provider identifier (NPI)	Claims
name_last	Provider last name	NPPES
name_first	Provider first name	NPPES
name_middle	Provider middle name	NPPES
Demographic variables		
sex	1=Male; 2=Female	NPPES
birth_dt	Birth date	PECOS
Specialty variables		
spec_broad	Broad specialty based on spec_prim_1 . 1 = Primary care 2 = Medical specialty 3 = Surgical specialty 4 = Obstetrics/gynecology with no primary care specialty. 5 = Hospital-based specialty (includes designated hospitalists) 6 = Psychiatry 7 = Non-physician 9 = Specialty Unknown	PECOS
spec_prim_1	Primary specialty (the most recently reported in PECOS)	PECOS/claims
spec_prim_1_name	Name of primary specialty	
spec_prim_2	Concurrently reported primary specialty	PECOS/claims
spec_prim_2_name	Name of concurrently reported primary specialty	
spec_source	Source data for specialty 1=PECOS 2=claims	PECOS/claims
spec_source_hosp	Source data for hospitalist specialty designation 1=PECOS 2=claims	PECOS/claims
Place of service (POS)		
pos_office	% of line items delivered in office	Claims
pos_inpat	% of line items delivered in inpatient hospital	Claims
pos_opd	% of line items delivered in hospital outpatient department (OPD)	Claims
pos_er	% of line items delivered in emergency room (ER)	Claims
pos_nursing	% of line items delivered in nursing facility or skilled nursing facility	Claims
pos_asc	% of line items delivered in ambulatory surgery center (ASC)	Claims
pos_resid	% of line items delivered in the patient's residence (i.e., home, assisted	Claims

Variable Name	Description	Data Source
	living facility, custodial care facility, or group home)	
pos_other	% of line items delivered in other places of service	Claims
Geographic location		
state	State abbreviation with the most line items for that NPI 99=missing	Claims
state_multi	Multiple state indicator (1=multiple states; 0=single state)	Claims
cbsa_type	Type of CBSA for physician 1=Metropolitan area 2=Micropolitan area 3=non-CBSA 9=missing CBSA code	Claims
cbsa_cd	CBSA code with the most allowed line items for that NPI 00000=non-CBSA 99999=missing CBSA code	Claims
cbsa_name	CBSA name	Claims
cbsa_multi	Multiple CBSA indicator (1=multiple CBSAs; 0=single CBSA)	Claims
Utilization summary measures		
npi_srvc_lines	Count of line items billed by NPI	Claims
npi_allowed_amt	Total allowed charges billed by NPI	Claims
npi_unq_benes	Number of unique beneficiaries for whom the NPI billed	Claims
TIN1 variables		
tin1	Tax identification number (TIN) with the most service lines	Claims
tin1_legal_name	TIN1 legal name	PECOS
tin1_srvc_month	Twelve monthly flags for whether the NPI billed for any services under TIN1. Position 1 pertains to January; position 12 to December. 1= billed 0= did not bill	Claims
tin1_srvc_lines	Count of line items billed under TIN1	Claims
tin1_allowed_amt	Total allowed charges billed under TIN1	Claims
tin1_unq_benes	Number of unique beneficiaries for whom the NPI billed under TIN1	Claims
TIN2 variables		
tin2	Tax identification number (TIN) with the most service lines	Claims
tin2_legal_name	TIN2 legal name	PECOS
tin2_srvc_month	Twelve monthly flags for whether the NPI billed for any services under TIN2. Position 1 pertains to January; position 12 to December. 1= billed 0= did not bill	Claims
tin2_srvc_lines	Count of line items billed under TIN2	Claims
tin2_allowed_amt	Total allowed charges billed under TIN2	Claims

Variable Name	Description	Data Source
tin2_unq_benes	Number of unique beneficiaries for whom the NPI billed under TIN2	Claims

Appendix H: Physician Count by County

County	2016 Physician Count
ADAIR	82
ANDREW	37
ATCHISON	6
AUDRAIN	34
BARRY	33
BARTON	18
BATES	12
BENTON	7
BOLLINGER	1
BOONE	1019
BUCHANAN	209
BUTLER	97
CALDWELL	2
CALLAWAY	30
CAMDEN	93
CAPE GIRARDEAU	362
CARROLL	6
CARTER	2
CASS	69
CEDAR	9
CHARITON	2
CHRISTIAN	55
CLARK	5
CLAY	584
CLINTON	5
COLE	273
COOPER	6
CRAWFORD	2
DADE	5
DALLAS	2
DAVIESS	3
DEKALB	23
DENT	8
DOUGLAS	3
DUNKLIN	18
FRANKLIN	149
GASCONADE	10
GENTRY	4
GREENE	1012

GRUNDY	8
HARRISON	6
HENRY	60
HICKORY	2
HOLT	2
HOWARD	3
HOWELL	92
IRON	8
JACKSON	2465
JASPER	385
JEFFERSON	161
JOHNSON	39
KNOX	0
LACLEDE	24
LAFAYETTE	18
LAWRENCE	17
LEWIS	5
LINCOLN	21
LINN	10
LIVINGSTON	21
MACON	12
MADISON	8
MARIES	2
MARION	115
MCDONALD	6
MERCER	1
MILLER	9
MISSISSIPPI	6
MONITEAU	3
MONROE	3
MONTGOMERY	2
MORGAN	7
NEW MADRID	4
NEWTON	19
NODAWAY	30
OREGON	2
OSAGE	2
OZARK	3
PEMISCOT	12
PERRY	17
PETTIS	57
PHELPS	100
PIKE	16
PLATTE	130
POLK	56

PULASKI	31
PUTNAM	5
RALLS	1
RANDOLPH	22
RAY	7
REYNOLDS	1
RIPLEY	0
SALINE	31
SCHUYLER	1
SCOTLAND	10
SCOTT	53
SHANNON	2
SHELBY	1
ST. CHARLES	540
ST. CLAIR	6
ST. FRANCOIS	87
STE GENEVIEVE	20
ST. LOUIS CITY	2673
ST. LOUIS COUNTY	3678
STODDARD	11
STONE	6
SULLIVAN	4
TANEY	109
TEXAS	19
VERNON	23
WARREN	9
WASHINGTON	17
WAYNE	5
WEBSTER	24
WORTH	1
WRIGHT	7

Appendix I: Hospital Access by County

County	**In County=1 <28 Miles=2 >27 Miles=3**	**2020 Licensed Beds**
Adair	1	93
Andrew	2	0
Atchison	1	18
Audrain	1	70
Barry	1	18
Barton	1	25
Bates	1	60
Benton	3	0
Bollinger	3	0
Boone	1	563
Buchanan	1	393
Butler	1	410
Caldwell	2	0
Callaway	1	37
Camden	1	130
Cape Girardeau	1	361
Carroll	1	25
Carter	3	0
Cass	1	106
Cedar	1	25
Chariton	2	0
Christian	2	0
Clark	2	0
Clay	1	873
Clinton	1	58
Cole	1	268
Cooper	1	32
Crawford	1	35
Dade	2	0
Dallas	3	0
Daviess	2	0
Dekalb	2	0
Dent	1	55
Douglas	3	0
Dunklin	1	116
Franklin	1	148
Gasconade	1	24

Gentry	1	35
Greene	1	1957
Grundy	1	25
Harrison	1	19
Henry	1	110
Hickory	3	0
Holt	2	0
Howard	2	0
Howell	1	139
Iron	1	15
Jackson	1	146
Jasper	1	3030
Jefferson	1	321
Johnson	1	62
Knox	2	0
Laclede	1	58
Lafayette	1	32
Lawrence	1	53
Lewis	3	0
Lincoln	1	25
Linn	1	25
Livingston	1	25
Macon	1	25
Madison	1	144
Maries	2	0
Marion	1	99
McDonald	3	0
Mercer	3	0
Miller	2	0
Mississippi	2	0
Moniteau	2	0
Monroe	3	0
Montgomery	2	0
Morgan	3	0
New Madrid	3	0
Newton	1	729
Nodaway	1	81
Oregon	3	0
Osage	2	0
Ozark	3	0
Pemiscot	1	167
Perry	1	25

Pettis	1	99
Phelps	1	242
Pike	1	25
Platte	1	97
Polk	1	86
Pulaski	3	0
Putnam	1	15
Ralls	2	0
Randolph	1	99
Ray	1	34
Reynolds	3	0
Ripley	1	30
Saline	1	60
Schuyler	2	0
Scotland	1	25
Scott	1	125
Shannon	3	0
Shelby	2	0
St. Charles	1	1016
St. Clair	1	12
Ste Genevieve	1	47
St. Francois	1	133
St. Louis City	1	2715
St. Louis County	1	4927
Stoddard	1	48
Stone	2	0
Sullivan	1	25
Taney	1	157
Texas	1	66
Vernon	1	140
Warren	2	0
Washington	1	25
Wayne	2	0
Webster	3	0
Worth	2	0
Wright	2	0

Appendix J: Correlations between MSBF and FFS Summary Data

Correlation between Encounter Summaries and MB Summaries of Service Activity
for FFS Beneficiaries in Sample

The CORR Procedure

Pearson Correlation Coefficients, N = 432765 Prob > |r| under H0: Rho=0	numipadmits	mbipadmits	numOPsrvcevents	HOP_VISITS	numcarsrvcrecs	mbcarevents	mbcarevents2
numipadmits	1.00000	0.99632 <.0001	0.29287 <.0001	0.29622 <.0001	0.49860 <.0001	0.57157 <.0001	0.54131 <.0001
mbipadmits	0.99632 <.0001	1.00000	0.29294 <.0001	0.29615 <.0001	0.49840 <.0001	0.57066 <.0001	0.54077 <.0001
numOPsrvcevents No. of OP/Service/Events	0.29287 <.0001	0.29294 <.0001	1.00000	0.99345 <.0001	0.37663 <.0001	0.39252 <.0001	0.40224 <.0001
HOP_VISITS Hospital Outpatient Visits	0.29622 <.0001	0.29615 <.0001	0.99345 <.0001	1.00000	0.37183 <.0001	0.38903 <.0001	0.39859 <.0001
numcarsrvcrecs	0.49860 <.0001	0.49840 <.0001	0.37663 <.0001	0.37183 <.0001	1.00000	0.92118 <.0001	0.93280 <.0001
mbcarevents	0.57157 <.0001	0.57066 <.0001	0.39252 <.0001	0.38903 <.0001	0.92118 <.0001	1.00000	0.97985 <.0001
mbcarevents2	0.54131 <.0001	0.54077 <.0001	0.40224 <.0001	0.39859 <.0001	0.93280 <.0001	0.97985 <.0001	1.00000
numhhasrvcrecs	0.36080 <.0001	0.36240 <.0001	0.12438 <.0001	0.12637 <.0001	0.22050 <.0001	0.26541 <.0001	0.25329 <.0001
HH_VISITS Home Health Visits	0.35657 <.0001	0.35806 <.0001	0.12450 <.0001	0.12635 <.0001	0.21892 <.0001	0.26386 <.0001	0.25131 <.0001
numsnfdiagevents	0.34008 <.0001	0.34014 <.0001	0.22270 <.0001	0.21959 <.0001	0.22959 <.0001	0.27930 <.0001	0.24064 <.0001
numsnfdischarges	0.51716 <.0001	0.51663 <.0001	0.22655 <.0001	0.22670 <.0001	0.30454 <.0001	0.36320 <.0001	0.32301 <.0001
SNF_STAYS Skilled Nursing Facility Stays	0.51709 <.0001	0.51656 <.0001	0.22648 <.0001	0.22663 <.0001	0.30449 <.0001	0.36313 <.0001	0.32296 <.0001
SNF_COV_DAYS Skilled Nursing Facility Covered Days	0.43739 <.0001	0.43675 <.0001	0.20685 <.0001	0.20685 <.0001	0.26398 <.0001	0.31325 <.0001	0.27607 <.0001

Correlation between MBSF and FFS Summary Data (continued)

Correlation between Encounter Summaries and MB Summaries of Service Activity
for FFS Beneficiaries in Sample

The CORR Procedure

Pearson Correlation Coefficients, N = 432765
Prob > |r| under H0: Rho=0

	numhhasrvcrecs	HH_VISITS	numsnfdiagevents	numsnfdischarges	SNF_STAYS	SNF_COV_DAYS
numipadmits	0.36080 <.0001	0.35657 <.0001	0.34008 <.0001	0.51716 <.0001	0.51709 <.0001	0.43739 <.0001
mbipadmits	0.36240 <.0001	0.35806 <.0001	0.34014 <.0001	0.51663 <.0001	0.51656 <.0001	0.43675 <.0001
numOPsrvcevents No. of OP/Service/Events	0.12438 <.0001	0.12450 <.0001	0.22270 <.0001	0.22655 <.0001	0.22648 <.0001	0.20685 <.0001
HOP_VISITS Hospital Outpatient Visits	0.12637 <.0001	0.12635 <.0001	0.21959 <.0001	0.22670 <.0001	0.22663 <.0001	0.20685 <.0001
numcarsrvcrecs	0.22050 <.0001	0.21892 <.0001	0.22959 <.0001	0.30454 <.0001	0.30449 <.0001	0.26398 <.0001
mbcarevents	0.26541 <.0001	0.26386 <.0001	0.27930 <.0001	0.36320 <.0001	0.36313 <.0001	0.31325 <.0001
mbcarevents2	0.25329 <.0001	0.25131 <.0001	0.24064 <.0001	0.32301 <.0001	0.32296 <.0001	0.27607 <.0001
numhhasrvcrecs	1.00000	0.97934 <.0001	0.14696 <.0001	0.25895 <.0001	0.25886 <.0001	0.22876 <.0001
HH_VISITS Home Health Visits	0.97934 <.0001	1.00000	0.15165 <.0001	0.26376 <.0001	0.26367 <.0001	0.23551 <.0001
numsnfdiagevents	0.14696 <.0001	0.15165 <.0001	1.00000	0.77147 <.0001	0.77139 <.0001	0.69211 <.0001
numsnfdischarges	0.25895 <.0001	0.26376 <.0001	0.77147 <.0001	1.00000	0.99988 <.0001	0.81674 <.0001
SNF_STAYS Skilled Nursing Facility Stays	0.25886 <.0001	0.26367 <.0001	0.77139 <.0001	0.99988 <.0001	1.00000	0.81664 <.0001
SNF_COV_DAYS Skilled Nursing Facility Covered Days	0.22876 <.0001	0.23551 <.0001	0.69211 <.0001	0.81674 <.0001	0.81664 <.0001	1.00000

Appendix K: FFS Sample Population Service Usage

Service Records for FFS 2016 Beneficiaries Meeting Sample Selection Criteria (Consolidated Daily) Excluding Zero Services in Tallies

	Instances					
	No. Benef	No. Records	Q1 per Benef	Median per Benef	Av. per Benef	Q3 per Benef
Service Type						
1:Inpatient Dschg	76,649	120,815	1.000	1.00	1.576	2.000
2:Outpatient Srvc	369,086	3,619,717	2.000	5.00	9.807	12.000
3:Outpatient Diag	369,086	2,611,675	2.000	5.00	7.076	9.000
4:Carrier Srvc	427,760	20,095,406	16.000	32.00	46.978	61.000
5:Carrier Diag	427,760	6,783,984	6.000	12.00	15.859	21.000
6:HHA Srvc	36,140	654,190	7.000	12.00	18.102	21.000
7:HHA Diag	34,191	41,313	1.000	1.00	1.208	1.000
8:SNF Diag	22,730	75,458	1.000	2.00	3.320	4.000

Service Records for FFS 2016 Beneficiaries Not Meeting Sample Selection Criteria (Consolidated Daily) Excluding Zero Services in Tallies

	Instances					
	No. Benef	No. Records	Q1 per Benef	Median per Benef	Av. per Benef	Q3 per Benef
Service Type						
1:Inpatient Dschg	42,885	83,769	1.000	1.00	1.953	2.000
2:Outpatient Srvc	124,687	2,157,181	3.000	7.00	17.301	15.000
3:Outpatient Diag	124,687	1,103,319	2.000	6.00	8.849	12.000
4:Carrier Srvc	177,905	7,352,696	6.000	21.00	41.329	53.000
5:Carrier Diag	177,905	2,574,182	2.000	8.00	14.469	20.000
6:HHA Srvc	13,634	241,262	6.000	12.00	17.696	22.000
7:HHA Diag	12,802	15,824	1.000	1.00	1.236	1.000
8:SNF Diag	10,941	33,474	1.000	2.00	3.060	4.000

Appendix L: HMO Sample Population Service Usage

Service Records for Medicare Advantage 2016 Beneficiaries Meeting Sample Selection Criteria (Consolidated Daily) Excluding Zero Services in Tallies

	Instances					
	No. Benef	No. Records	Q1 per Benef	Median per Benef	Av. per Benef	Q3 per Benef
Service Type						
1:Inpatient Dschg	30,519	46,418	1.000	1.00	1.521	2.000
2:Outpatient Srvc	166,637	971,540	2.000	3.00	5.830	7.000
3:Outpatient Diag	166,638	824,611	2.000	3.00	4.949	6.000
4:Carrier Srvc	212,683	9,132,165	17.000	31.00	42.938	54.000
5:Carrier Diag	212,683	2,933,694	6.000	10.00	13.794	18.000
6:HHA Srvc	14,548	171,469	3.000	8.00	11.786	14.000
7:HHA Diag	14,570	39,198	1.000	2.00	2.690	3.000
8:SNF Diag	8,249	16,000	1.000	2.00	1.940	2.000

Service Records for Medicare Advantage 2016 Beneficiaries NOT Meeting Sample Selection Criteria (Consolidated Daily) Excluding Zero Services in Tallies

	Instances					
	No. Benef	No. Records	Q1 per Benef	Median per Benef	Av. per Benef	Q3 per Benef
Service Type						
1:Inpatient Dschg	16,242	29,070	1.000	1.00	1.790	2.000
2:Outpatient Srvc	52,577	462,903	2.000	4.00	8.804	9.000
3:Outpatient Diag	52,577	332,797	2.000	4.00	6.330	8.000
4:Carrier Srvc	65,515	3,169,362	14.000	32.00	48.376	61.000
5:Carrier Diag	65,515	1,027,169	5.000	11.00	15.678	21.000
6:HHA Srvc	5,384	57,800	2.000	7.00	10.736	14.000
7:HHA Diag	5,397	14,309	1.000	2.00	2.651	3.000
8:SNF Diag	3,962	8,019	1.000	2.00	2.024	2.000

Appendix M: Tabular Results for Plan Choice CHAID Tree

Tree Table

Node	Aetna		Essence		Humana		None		Other		UHC		Total		Predicted Category	Parent Node	Primary Independent Variable				
	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent	N	Percent			Variable	Sig.[a]	Chi-Square	df	Split Values
0	18337	3.8%	25074	5.2%	20956	4.3%	324151	66.9%	72655	15.0%	23228	4.8%	484401	100.0%	None						
1	871	0.9%	488	0.5%	2707	2.8%	74578	78.1%	14799	15.5%	2018	2.1%	95461	19.7%	None	0	physicians2016	.000	80560.808	20	<= 18.0
2	774	0.8%	1663	1.7%	5021	5.0%	74335	73.9%	17464	17.4%	1356	1.3%	100613	20.8%	None	0	physicians2016	.000	80560.808	20	(18.0, 109.0]
3	7112	8.0%	5842	6.5%	2072	2.3%	57518	64.5%	9472	10.6%	7216	8.1%	89232	18.4%	None	0	physicians2016	.000	80560.808	20	(109.0, 540.0]
4	91	0.1%	2761	2.9%	9992	10.4%	58721	60.8%	22326	23.1%	2615	2.7%	96506	19.9%	None	0	physicians2016	.000	80560.808	20	(540.0, 2465.0]
5	9489	9.2%	14320	14.0%	1164	1.1%	58999	57.5%	8594	8.4%	10023	9.8%	102589	21.2%	None	0	physicians2016	.000	80560.808	20	> 2465.0
6	266	0.6%	9	0.0%	1335	2.8%	38092	79.8%	6940	14.5%	1100	2.3%	47742	9.9%	None	1	Hosp_access_index	.000	2457.383	10	1.0
7	2	0.0%	10	0.0%	640	3.0%	16349	77.0%	4057	19.1%	164	0.8%	21222	4.4%	None	1	Hosp_access_index	.000	2457.383	10	3.0
8	603	2.3%	469	1.8%	732	2.8%	20137	76.0%	3802	14.3%	754	2.8%	26497	5.5%	None	1	Hosp_access_index	.000	2457.383	10	2.0
9	68	0.2%	3	0.0%	932	3.0%	25944	82.3%	4422	14.0%	169	0.5%	31538	6.5%	None	2	medianhouseeval	.000	2270.889	5	<= 96.800
10	706	1.0%	1660	2.4%	4089	5.9%	48391	70.1%	13042	18.9%	1187	1.7%	69075	14.3%	None	2	medianhouseeval	.000	2270.889	5	> 96.800
11	174	0.6%	1	0.0%	761	2.6%	25169	85.7%	3252	11.1%	5	0.0%	29362	6.1%	None	3	medianhouseeval	.000	14186.056	10	<= 146.800
12	3338	13.2%	3397	13.4%	365	1.4%	12229	48.2%	2375	9.4%	3664	14.4%	25368	5.2%	None	3	medianhouseeval	.000	14186.056	10	(146.800, 161.000]
13	3600	10.4%	2444	7.1%	946	2.7%	20120	58.3%	3845	11.1%	3547	10.3%	34502	7.1%	None	3	medianhouseeval	.000	14186.056	10	> 161.000
14	7	0.0%	2116	3.0%	8416	12.0%	38647	55.0%	18890	26.9%	2176	3.1%	70252	14.5%	None	4	medianhouseeval	.000	4036.602	5	<= 146.800
15	84	0.3%	645	2.5%	1576	6.0%	20074	76.5%	3436	13.1%	439	1.7%	26254	5.4%	None	4	medianhouseeval	.000	4036.602	5	> 146.800
16	2734	9.4%	2738	9.4%	326	1.1%	18315	62.9%	2511	8.6%	2508	8.6%	29132	6.0%	None	5	maxchscoreallserv	.000	1418.131	10	<= .0
17	4259	9.3%	6424	14.0%	528	1.1%	26748	58.2%	3727	8.1%	4308	9.4%	45994	9.5%	None	5	maxchscoreallserv	.000	1418.131	10	(.0, 3.0]
18	2496	9.1%	5158	18.8%	310	1.1%	13936	50.7%	2356	8.6%	3207	11.7%	27463	5.7%	None	5	maxchscoreallserv	.000	1418.131	10	> 3.0
19	182	0.8%	6	0.0%	657	2.8%	18075	78.0%	3581	15.4%	682	2.9%	23183	4.8%	None	6	zpctbachelorsormore	.000	167.384	5	<= 14.500
20	84	0.3%	3	0.0%	678	2.8%	20017	81.5%	3359	13.7%	418	1.7%	24559	5.1%	None	6	zpctbachelorsormore	.000	167.384	5	> 14.500, <missing>
21	644	1.8%	828	2.4%	2115	6.1%	24105	69.0%	6646	19.0%	609	1.7%	34947	7.2%	None	10	zpctbachelorsormore	.000	481.287	5	<= 20.200
22	62	0.2%	832	2.4%	1974	5.8%	24286	71.2%	6396	18.7%	578	1.7%	34128	7.0%	None	10	zpctbachelorsormore	.000	481.287	5	> 20.200, <missing>
23	5	0.0%	1407	2.9%	6656	13.6%	25778	52.5%	13694	27.9%	1533	3.1%	49073	10.1%	None	14	zpctbachelorsormore	.000	597.364	5	<= 40.200
24	2	0.0%	709	3.3%	1760	8.3%	12869	60.8%	5196	24.5%	643	3.0%	21179	4.4%	None	14	zpctbachelorsormore	.000	597.364	5	> 40.200, <missing>
25	1994	9.2%	4236	19.6%	338	1.6%	10996	50.8%	1766	8.2%	2301	10.6%	21631	4.5%	None	17	zpctbachelorsormore	.000	1430.328	5	<= 40.200
26	2265	9.3%	2188	9.0%	190	0.8%	15752	64.7%	1961	8.0%	2007	8.2%	24363	5.0%	None	17	zpctbachelorsormore	.000	1430.328	5	> 40.200, <missing>

Growing Method: CHAID
Dependent Variable: maplanchoice

a. Bonferroni adjusted

Appendix N: Poisson Regressions Tables Before Variable Reduction

All Plans

Poisson Regression Model for Number of Inpatient Discharges per Patient over One Year for 2016 ALL Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.3082	0.03390	0.03658	-97.597	.0000
maxchscoreallserv	0.2547	0.000709	1.29001	358.934	.0000
female	0.08192	0.005774	1.08537	14.188	.0000
HMOplan	-0.3576	0.006473	0.69937	-55.238	.0000
yrendage	0.01723	0.000363	1.01738	47.482	.0000
Black	-0.01893	0.01135	0.98124	-1.668	.0953
Hispanic	0.08351	0.06589	1.08710	1.268	.2050
Asian	-0.3099	0.05375	0.73353	-5.766	.0000
Othernonwhite	-0.2065	0.02841	0.81340	-7.269	.0000
medianhousevaI	-0.00123	0.000097	0.99877	-12.662	.0000
zpctbachelorsormore	0.000504	0.000565	1.00050	0.892	.3723
zpctmanprofoccs	-0.00198	0.000715	0.99803	-2.763	.0057
hospitalaccess1	0.1022	0.01368	1.10758	7.469	.0000
hospitalaccess2	-0.00134	0.01675	0.99866	-0.080	.9362
physicianper1000	0.000304	0.001797	1.00030	0.169	.8656

Poisson Regression Model for Number of Outpatient Service Events per Patient over One Year for 2016 ALL Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.0658	0.006369	2.90314	167.35	.0000
maxchscoreallserv	0.1656	0.000163	1.18009	1014.99	.0000
female	0.2122	0.001118	1.23643	189.75	.0000
HMOplan	-0.6223	0.001349	0.53670	-461.19	.0000
yrendage	0.01062	0.000070	1.01067	152.22	.0000
Black	-0.07017	0.002431	0.93224	-28.86	.0000
Hispanic	-0.09815	0.01376	0.90651	-7.13	.0000
Asian	-0.2765	0.009883	0.75845	-27.97	.0000
Othernonwhite	-0.07731	0.004936	0.92560	-15.66	.0000
medianhouseval	-0.00340	0.000019	0.99661	-181.15	.0000
zpctbachelorsormore	0.000616	0.000104	1.00062	5.94	.0000
zpctmanprofoccc	0.003188	0.000130	1.00319	24.47	.0000
hospitalaccess1	0.09762	0.002431	1.10254	40.16	.0000
hospitalaccess2	0.03418	0.002946	1.03477	11.60	.0000
physiciansper1000	-0.03800	0.000368	0.96271	-103.23	.0000

Poisson Regression Model for Number of Carrier Services with Diagnostics over One Year for 2016 ALL Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.7724	0.004510	5.88517	392.96	.0000
maxchsccreallserv	0.1389	0.000118	1.14904	1176.87	.0000
female	0.1309	0.000764	1.13989	171.44	.0000
HMOplan	-0.1953	0.000826	0.82259	-236.42	.0000
yrendage	0.004503	0.000049	1.00451	91.93	.0000
Black	-0.1639	0.001605	0.84887	-102.11	.0000
Hispanic	-0.1796	0.009725	0.83562	-18.47	.0000
Asian	-0.3502	0.006569	0.70457	-53.31	.0000
Othernonwhite	-0.1006	0.003255	0.90433	-30.89	.0000
medianhouseeval	0.000783	0.000013	1.00078	61.00	.0000
zpctbachelorsormore	0.005163	0.000074	1.00518	69.97	.0000
zpctmanprofoccs	-0.00250	0.000095	0.99751	-26.33	.0000
hospitalaccess1	0.04805	0.001869	1.04922	25.71	.0000
hospitalaccess2	0.03849	0.002233	1.03924	17.23	.0000
physiciansper1000	0.005579	0.000240	1.00559	23.20	.0000

Poisson Regression Model for Number of Home Health Assistance Services over One Year for 2016 ALL Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-4.8312	0.01501	0.00798	-321.967	.0000
maxohscorealiserv	0.2403	0.000335	1.27164	716.748	.0000
female	0.3135	0.002689	1.36815	116.577	.0000
HMOplan	-0.7462	0.003205	0.47416	-232.835	.0000
yrendage	0.05542	0.000153	1.05699	361.391	.0000
Black	0.2116	0.004768	1.23559	44.372	.0000
Hispanic	-0.1642	0.03281	0.84858	-5.004	.0000
Asian	-0.1341	0.02227	0.87450	-6.022	.0000
Othernonwhite	-0.02270	0.01312	0.97756	-1.730	.0837
medianhouseval	0.000017	0.000044	1.00002	0.388	.6981
zpctbachelorsormore	-0.00194	0.000256	0.99806	-7.579	.0000
zpctmanprofoccs	-0.00146	0.000325	0.99854	-4.502	.0000
hospitalaccess1	0.04214	0.006231	1.04304	6.763	.0000
hospitalaccess2	0.02585	0.007554	1.02619	3.422	.0006
physiciansper1000	0.01946	0.000783	1.01965	24.843	.0000

Poisson Regression Model for Number of Skilled Nursing Facility Services with Diagnostics over One Year for 2016 ALL Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-8.3500	0.04499	0.00024	-185.597	.0000
maxchccreallserv	0.2602	0.000989	1.29714	263.010	.0000
female	0.4536	0.008299	1.57404	54.661	.0000
HMOplan	-0.8687	0.01026	0.41948	-84.651	.0000
yrendage	0.07638	0.000458	1.07937	166.930	.0000
Black	-0.02757	0.01618	0.97280	-1.704	.0884
Hispanic	-0.07279	0.09296	0.92980	-0.783	.4336
Asian	-0.3601	0.07923	0.69758	-4.545	.0000
Othernonwhite	-0.3734	0.05049	0.68838	-7.396	.0000
medianhouseval	-0.00310	0.000132	0.99691	-23.387	.0000
zpctbachelorsormore	-0.00153	0.000764	0.99847	-2.004	.0450
zpctmanprofoccs	-0.00587	0.000955	0.99415	-6.141	.0000
hospitalaccess1	0.1407	0.01775	1.15112	7.929	.0000
hospitalaccess2	0.1040	0.02145	1.10955	4.847	.0000
physiciansper1000	-0.00427	0.002447	0.99574	-1.744	.0811

FFS Plan Only

Poisson Regression Model for Number of Inpatient Discharges per Patient over One Year for 2016 FFS Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.4241	0.03913	0.03258	-87.499	.0000
maxohscoreallserv	0.2561	0.000839	1.29194	305.158	.0000
female	0.07170	0.006795	1.07433	10.552	.0000
yrendage	0.01776	0.000418	1.01792	42.468	.0000
Black	0.02178	0.01416	1.02202	1.538	.1240
Hispanic	0.1048	0.07635	1.11047	1.372	.1700
Asian	-0.2622	0.05994	0.76935	-4.375	.0000
Othernonwhite	-0.2287	0.03332	0.79557	-6.864	.0000
medianhouseval	-0.00076	0.000114	0.99924	-6.702	.0000
zpctbachelorsormore	-0.00074	0.000648	0.99926	-1.142	.2533
zpctmanprofoccs	-0.00141	0.000818	0.99859	-1.728	.0840
hospitalaccess1	0.1122	0.01553	1.11873	7.225	.0000
hospitalaccess2	-0.00539	0.01909	0.99463	-0.282	.7779
physicianper1000	0.006670	0.002119	1.00669	3.148	.0016

Poisson Regression Model for Number of Outpatient Service Events per Patient over One Year for 2016 FFS Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	0.8108	0.007047	2.24970	115.050	.0000
maxchccrealiserv	0.1665	0.000185	1.18119	899.156	.0000
female	0.2212	0.001263	1.24757	175.180	.0000
yrendage	0.01366	0.000077	1.01375	177.797	.0000
Black	-0.07365	0.002930	0.92899	-25.138	.0000
Hispanic	-0.1144	0.01555	0.89193	-7.357	.0000
Asian	-0.2781	0.01096	0.75721	-25.365	.0000
Othernonwhite	-0.07134	0.005533	0.93115	-12.892	.0000
medianhouseval	-0.00322	0.000021	0.99679	-152.407	.0000
zpctbachelorsormore	0.000453	0.000115	1.00045	3.948	.0001
zpctmanprofoccs	0.002420	0.000144	1.00242	16.781	.0000
hospitalaccess1	0.1043	0.002670	1.10991	39.063	.0000
hospitalaccess2	0.04290	0.003234	1.04384	13.267	.0000
physiciansper1000	-0.03148	0.000417	0.96901	-75.510	.0000

Poisson Regression Model for Number of Carrier Services with Diagnostics over One Year for 2016 FFS Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
intercept	1.6672	0.005277	5.29729	315.931	.0000
maxchsccreallserv	0.1413	0.000143	1.15175	989.677	.0000
female	0.1407	0.000916	1.15109	153.566	.0000
yrendage	0.004909	0.000057	1.00492	85.562	.0000
Black	-0.1809	0.002106	0.83454	-85.880	.0000
Hispanic	-0.2064	0.01173	0.81347	-17.598	.0000
Asian	-0.3682	0.007697	0.69195	-47.844	.0000
Othernonwhite	-0.1082	0.003846	0.89749	-28.121	.0000
medianhouseval	0.001110	0.000015	1.00111	72.891	.0000
zpctbachelorsormore	0.004791	0.000086	1.00480	55.877	.0000
zpctmanprofoccs	-0.00201	0.000110	0.99799	-18.261	.0000
hospitalaccess1	0.04454	0.002148	1.04554	20.735	.0000
hospitalaccess2	0.04095	0.002573	1.04180	15.916	.0000
physiciansper1000	0.01149	0.000288	1.01155	39.908	.0000

Poisson Regression Model for Number of Home Health Assistance Services over One Year for 2016 FFS Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-4.9163	0.01663	0.00733	-295.596	.0000
maxohccorealiserv	0.2434	0.000377	1.27555	645.293	.0000
female	0.3149	0.003027	1.37015	104.050	.0000
yrendage	0.05461	0.000170	1.05613	321.449	.0000
Black	0.3122	0.005408	1.36639	57.720	.0000
Hispanic	-0.1917	0.03773	0.82554	-5.082	.0000
Asian	-0.05555	0.02336	0.94596	-2.378	.0174
Othernonwhite	0.004437	0.01442	1.00445	0.308	.7584
medianhouseval	0.000942	0.000049	1.00094	19.373	.0000
zpctbachelorsormore	-0.00437	0.000282	0.99564	-15.464	.0000
zpctmanprofoccs	0.000638	0.000358	1.00064	1.783	.0745
hospitalaccess1	0.01362	0.006805	1.01371	2.001	.0454
hospitalaccess2	0.01684	0.008264	1.01698	2.038	.0416
physiciansper1000	0.02835	0.000873	1.02875	32.477	.0000

Poisson Regression Model for Number of Skilled Nursing Facility Services with Diagnostics over One Year for 2016 FFS Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-8.3989	0.04902	0.00023	-171.347	.0000
maxchscoreallserv	0.2600	0.001099	1.29698	236.583	.0000
female	0.4598	0.009189	1.58383	50.041	.0000
yrendage	0.07731	0.000499	1.08038	155.065	.0000
Black	0.04025	0.01836	1.04107	2.192	.0284
Hispanic	-0.05306	0.1027	0.94833	-0.516	.6055
Asian	-0.3060	0.08383	0.73642	-3.650	.0003
Othernonwhite	-0.4454	0.05790	0.64054	-7.694	.0000
medianhouseval	-0.00291	0.000146	0.99709	-19.973	.0000
zpctbachelorsormore	-0.00298	0.000830	0.99702	-3.591	.0003
zpctmanprofoccs	-0.00675	0.001033	0.99327	-6.536	.0000
hospitalaccess1	0.1320	0.01891	1.14110	6.978	.0000
hospitalaccess2	0.1214	0.02279	1.12909	5.328	.0000
physiciansper1000	0.002316	0.002700	1.00232	0.858	.3909

All HMO Plans

Poisson Regression Model for Number of Inpatient Discharges per Patient over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.3127	0.06804	0.03642	-48.691	.0000
maxchscoreallserv	0.2512	0.001326	1.28561	189.400	.0000
female	0.1100	0.01096	1.11625	10.032	.0000
yrendage	0.01627	0.000732	1.01640	22.241	.0000
Black	-0.06402	0.01902	0.93799	-3.367	.0008
Hispanic	0.02498	0.1304	1.02530	0.192	.8480
Asian	-0.4985	0.1215	0.60745	-4.103	.0000
Othernonwhite	-0.1411	0.05439	0.86843	-2.593	.0095
medianhouseeval	-0.00277	0.000190	0.99724	-14.547	.0000
zpctbachelorsormore	0.004131	0.001154	1.00414	3.579	.0003
zpctmanprofoccs	-0.00426	0.001466	0.99575	-2.906	.0037
hospitalaccess1	0.07597	0.02895	1.07893	2.624	.0087
hospitalaccess2	0.02156	0.03498	1.02179	0.616	.5377
physicianper1000	-0.01865	0.003403	0.98152	-5.481	.0000

Poisson Regression Model for Number of Outpatient Service Events per Patient over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.5907	0.01497	4.90719	106.283	.0000
maxohscoreallserv	0.1638	0.000344	1.17798	475.997	.0000
female	0.1718	0.002414	1.18747	71.186	.0000
yrendage	-0.00304	0.000167	0.99697	-18.194	.0000
Black	-0.04677	0.004390	0.95431	-10.653	.0000
Hispanic	-0.02036	0.02957	0.97985	-0.689	.4911
Asian	-0.3024	0.02283	0.73901	-13.248	.0000
Othernonwhite	-0.09626	0.01093	0.90823	-8.811	.0000
medianhouseval	-0.00409	0.000041	0.99592	-98.872	.0000
zpctbachelorsormore	0.000805	0.000240	1.00081	3.362	.0008
zpctmanprofoccs	0.006096	0.000303	1.00611	20.096	.0000
hospitalaccess1	0.05565	0.005892	1.05723	9.446	.0000
hospitalaccess2	-0.00862	0.007154	0.99142	-1.205	.2283
physicianper1000	-0.05752	0.000786	0.94411	-73.136	.0000

Poisson Regression Model for Number of Carrier Services with Diagnostics over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.8691	0.008719	6.48259	214.374	.0000
maxchscoreallserv	0.1343	0.000210	1.14374	640.337	.0000
female	0.1089	0.001383	1.11503	78.702	.0000
yrendage	0.003678	0.000094	1.00368	38.994	.0000
Black	-0.1253	0.002504	0.88226	-50.034	.0000
Hispanic	-0.1179	0.01739	0.88877	-6.781	.0000
Asian	-0.3146	0.01260	0.73008	-24.960	.0000
Othernonwhite	-0.08011	0.006111	0.92301	-13.108	.0000
medianhouseval	-0.00025	0.000024	0.99975	-10.366	.0000
zpctbachelorsormore	0.006127	0.000145	1.00615	42.318	.0000
zpctmanprofoccs	-0.00392	0.000186	0.99609	-21.050	.0000
hospitalaccess1	0.06422	0.003798	1.06633	16.908	.0000
hospitalaccess2	0.04059	0.004507	1.04143	9.008	.0000
physiciansper1000	-0.01096	0.000441	0.98910	-24.847	.0000

Poisson Regression Model for Number of Home Health Assistance Services over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-5.1856	0.03474	0.00560	-149.260	.0000
maxohscoreallserv	0.2298	0.000731	1.25835	314.576	.0000
female	0.3170	0.005861	1.37306	54.092	.0000
yrendage	0.06044	0.000357	1.06230	169.084	.0000
Black	-0.03471	0.009953	0.96588	-3.488	.0005
Hispanic	-0.09836	0.06648	0.90633	-1.480	.1390
Asian	-0.7273	0.07401	0.48320	-9.827	.0000
Othernonwhite	-0.1477	0.03161	0.86272	-4.671	.0000
medianhouseval	-0.00467	0.000099	0.99534	-47.300	.0000
zpctbachelorsormore	0.009161	0.000607	1.00920	15.082	.0000
zpctmanprofoccs	-0.01247	0.000772	0.98761	-16.158	.0000
hospitalaccess1	0.2287	0.01553	1.25696	14.721	.0000
hospitalaccess2	0.1287	0.01867	1.13736	6.894	.0000
physiciansper1000	-0.02833	0.001758	0.97206	-16.114	.0000

Poisson Regression Model for Number of Skilled Nursing Facility Services with Diagnostics over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-8.9228	0.1144	0.00013	-78.014	.0000
maxchscoreallserv	0.2614	0.002268	1.29881	115.274	.0000
female	0.4251	0.01936	1.52979	21.961	.0000
yrendage	0.07120	0.001159	1.07380	61.436	.0000
Black	-0.1958	0.03393	0.82216	-5.771	.0000
Hispanic	-0.1557	0.2186	0.85580	-0.712	.4762
Asian	-0.7128	0.2428	0.49028	-2.935	.0033
Othernonwhite	-0.1001	0.1033	0.90475	-0.969	.3323
medianhouseeval	-0.00386	0.000323	0.99614	-11.974	.0000
zpctbachelorsormore	0.004452	0.001979	1.00446	2.249	.0245
zpctmanprofoccs	-0.00248	0.002526	0.99753	-0.981	.3268
hospitalaccess1	0.1970	0.05154	1.21780	3.823	.0001
hospitalaccess2	-0.02577	0.06356	0.97456	-0.405	.6851
physicianper1000	-0.03044	0.005775	0.97002	-5.270	.0000

Essence HMO

Poisson Regression Model for Number of Inpatient Discharges per Patient over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-3.2981	0.4497	0.03695	-7.3348	.0000
maxchscoreallserv	0.2344	0.004047	1.26419	57.9254	.0000
female	0.1233	0.03140	1.13121	3.9264	.0001
yrendage	0.01376	0.002109	1.01385	6.5242	.0000
Black	-0.08682	0.04769	0.91684	-1.8206	.0687
Hispanic	0.3776	0.4091	1.45874	0.9230	.3560
Asian	-0.7796	0.4478	0.45859	-1.7408	.0817
Othernonwhite	-0.2257	0.1575	0.79792	-1.4331	.1518
medianhouseval	-0.00098	0.000760	0.99902	-1.2939	.1957
zpctbachelorsormore	-0.00886	0.004437	0.99118	-1.9957	.0460
zpctmanprofoccs	0.01024	0.005744	1.01029	1.7830	.0746
hospitalaccess1	-0.4256	0.4135	0.65336	-1.0293	.3034
hospitalaccess2	-0.1857	0.4167	0.83050	-0.4457	.6558
physicianper1000	-0.00213	0.009592	0.99787	-0.2220	.8243

Poisson Regression Model for Number of Outpatient Service Events per Patient over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	2.2184	0.09875	9.19293	22.466	.0000
maxchscoreallserv	0.1533	0.001049	1.16565	146.174	.0000
female	0.2311	0.007080	1.26002	32.644	.0000
yrendage	-0.01002	0.000499	0.99003	-20.097	.0000
Black	-0.09722	0.01115	0.90736	-8.716	.0000
Hispanic	0.1013	0.1119	1.10662	0.905	.3654
Asian	-0.1000	0.06210	0.90480	-1.611	.1072
Othernonwhite	-0.04922	0.02988	0.95197	-1.647	.0995
medianhouseeval	-0.00618	0.000164	0.99384	-37.764	.0000
zpctbachelorsormore	0.008609	0.000932	1.00865	9.239	.0000
zpctmanprofoccs	-0.00353	0.001214	0.99648	-2.909	.0036
hospitalaccess1	0.1216	0.09012	1.12934	1.350	.1771
hospitalaccess2	0.5345	0.09037	1.70652	5.914	.0000
physiciansper1000	-0.04594	0.002109	0.95509	-21.782	.0000

Poisson Regression Model for Number of Carrier Services with Diagnostics over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	1.9119	0.05653	6.76561	33.820	.0000
maxchscoreallserv	0.1247	0.000574	1.13278	217.210	.0000
female	0.1009	0.003654	1.10615	27.612	.0000
yrendage	0.002632	0.000252	1.00264	10.430	.0000
Black	-0.1607	0.005760	0.85156	-27.896	.0000
Hispanic	-0.1141	0.06256	0.89214	-1.824	.0681
Asian	-0.2059	0.03362	0.81393	-6.124	.0000
Othernonwhite	-0.07508	0.01580	0.92767	-4.752	.0000
medianhouseeval	-0.00024	0.000088	0.99976	-2.711	.0067
zpctbachelorsormore	-0.00019	0.000500	0.99981	-0.381	.7031
zpctmanprofoccs	0.003205	0.000654	1.00321	4.904	.0000
hospitalaccess1	-0.06402	0.05251	0.93798	-1.219	.2227
hospitalaccess2	-0.03010	0.05290	0.97035	-0.569	.5693
physicianper1000	-0.00850	0.001130	0.99153	-7.522	.0000

Poisson Regression Model for Number of Home Health Assistance Services over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-2.9819	0.2724	0.05069	-10.9480	.0000
maxchscoreallserv	0.1896	0.003090	1.20874	61.3608	.0000
female	0.3344	0.02247	1.39706	14.8827	.0000
yrendage	0.04440	0.001403	1.04540	31.6387	.0000
Black	-0.5394	0.04078	0.58307	-13.2278	.0000
Hispanic	-0.4710	0.3785	0.62438	-1.2445	.2133
Asian	-21.0703	8061.93	0.00000	-0.0026	.9979
Othernonwhite	-0.2343	0.1141	0.79111	-2.0537	.0400
medianhouseval	-0.01310	0.000486	0.98698	-26.9500	.0000
zpctbachelorsormore	0.007867	0.002979	1.00790	2.6408	.0083
zpctmanprofoccs	-0.00747	0.003865	0.99256	-1.9316	.0534
hospitalaccess1	0.05594	0.2458	1.05753	0.2276	.8200
hospitalaccess2	0.1528	0.2480	1.16508	0.6162	.5378
physiciansper1000	-0.06935	0.006310	0.93300	-10.9915	.0000

Poisson Regression Model for Number of Skilled Nursing Facility Services with Diagnostics over One Year for 2016 HMO Beneficiaries

Explanatory Variable	Parameter Estimate for log(mean)	Std. Error of Parameter Estimate)	Factor For Incidence Impact	Value of Z Statistic	P-value two-tail test
Intercept	-8.5300	0.8024	0.00020	-10.6303	.0000
maxchscorealiserv	0.2567	0.008201	1.29267	31.3007	.0000
female	0.4097	0.06701	1.50634	6.1133	.0000
yrendage	0.06963	0.003998	1.07211	17.4169	.0000
Black	-0.3688	0.1063	0.69157	-3.4698	.0005
Hispanic	0.9263	0.5034	2.52526	1.8402	.0657
Asian	-19.7307	13620	0.00000	-0.0014	.9988
Othernonwhite	-0.4715	0.4104	0.62406	-1.1490	.2506
medianhouseval	-0.00100	0.001584	0.99900	-0.6287	.5296
zpctbachelorsormore	0.008488	0.009270	1.00852	0.9156	.3599
zpctmanprofoccs	-0.00813	0.01222	0.99191	-0.6647	.5062
hospitalaccess1	-1.0759	0.7208	0.34099	-1.4927	.1355
hospitalaccess2	-1.1745	0.7371	0.30898	-1.5934	.1111
physicianper1000	-0.01797	0.01992	0.98219	-0.9020	.3670