Healthcare Spending and Utilization in Public and Private Medicare*

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Abstract. We compare healthcare spending in public and private Medicare using newly available claims data from Medicare Advantage (MA) insurers. MA insurer revenues are 30 percent higher than their healthcare spending. Healthcare spending is 25 percent lower for MA enrollees than for enrollees in traditional Medicare (TM) in the same county with the same risk score. Spending differences between MA and TM are similar across sub-populations of enrollees and sub-categories of care, with similar reductions for "high value" and "low value" care. Spending differences primarily reflect differences in healthcare utilization; spending per encounter and hospital payments per admission are very similar in MA and TM. Geographic variation in MA spending is about 20 percent higher than in TM, but geographic variation in hospital prices is about 20 percent lower. We present evidence consistent with MA plans encouraging substitution to less expensive care, such as primary rather than specialist care, and outpatient rather than inpatient surgery, and with employing various types of utilization management. Some of the overall spending differences between MA and TM may be driven by selection on unobservables, and we report a range of estimates of this selection effect using mortality outcomes to proxy for selection.

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1 Introduction

A long-standing question in economics concerns the appropriate roles of the public sector and private sector in providing services that society has decided are essential. This question comes up in many contexts, including education, utilities, transportation, and pensions. It is especially relevant in healthcare, where the United States is unusual among developed countries in its distinctive mix of public and private health insurance. Comparisons of public and private health insurance systems are difficult, however, since they typically do not operate at a similar scale for the same population, in the same markets, or with the same healthcare providers.

The U.S. Medicare program in recent years has been an exception because of the "side by side" operation of public and private insurance programs. While traditional Medicare (TM) offers publicly administered insurance, a significant fraction of the over-65 Medicare population has opted out of TM in the last decade and enrolled in private insurance plans through Medicare Advantage (MA). In MA, private insurers receive capitated payments from the government for providing Medicare beneficiaries with health insurance that roughly mimics commercial health insurance for the under-65 population. Today almost a third of Medicare beneficiaries are enrolled in MA.

Empirical comparisons of MA and TM have been hampered by asymmetric data availability: administrative claim-level data from TM is widely available to researchers, but detailed claim-level data from MA insurers has been more elusive. In this paper, we take advantage of newly available claims data from Medicare Advantage plans in 2010 provided by the Health Care Cost Institute (HCCI). The data consist of claims paid by three Medicare Advantage insurers (Aetna, Humana, and UnitedHealthcare) that cover almost 40 percent of MA enrollees. The key advantage of these data is that they contain claim-level data in MA – i.e. healthcare utilization and payments to providers – that is analogous to the existing and commonly used claims data for TM.

A simple tabulation of the MA and TM claims points to a large difference in public and private healthcare spending levels. We calculate that MA spending per enrollee-month totaled \$642, of which \$590 was paid by MA insurers and the rest by enrollees out-of-pocket. In contrast, average spending per enrollee-month in TM was \$911, of which \$771 was paid directly by the Medicare program to providers. Capitated payments to the MA plans roughly track the latter number. The MA plans in the HCCI data received on average \$767 per enrollee-month, or \$177 (30 percent) more than MA insurer payments for healthcare.

A more appropriate comparison of MA and TM spending adjusts for differences in their enrollee populations. Our baseline analysis compares MA and TM enrollees in the same county and with the same risk score. Medicare risk scores are based on a predictive model of healthcare spending that accounts for demographics and detailed information on prior health conditions. The county and risk score adjustment capture the spirit in which Medicare sets reimbursement rates for MA insurers; these are the two dimensions used in tailoring capitation rates.

Holding county and risk score fixed, we find that healthcare spending for MA enrollees is 25 percent lower than for TM enrollees. The difference is similar when we focus on sub-populations of enrollees defined by age, by gender, or by residence in urban versus rural counties. The proportional difference in spending is also similar across quantiles of the spending distribution. Spending differences between MA and TM are similar for inpatient and outpatient care.

We decompose the overall spending difference into differences in healthcare utilization and differences in payment rates. Lower spending in MA primarily reflects lower utilization of services. Lower utilization appears across the board. MA enrollees have fewer inpatient admissions, fewer outpatient office visits, fewer skilled nursing facility visits, fewer physician visits, and fewer emergency department visits. MA enrollees have lower utilization for services where there are concerns about over-use, such as diagnostic testing and imaging, and for services where there are concerns about under-use, such as preventive care.

In contrast, we find little difference in the average prices paid for services in MA and TM. Hospital payments per admission and per day are within one percent for MA and TM. To account for potential differences in the types of hospital admissions and the hospitals used by MA and TM enrollees, we compare payments made to the same hospital for the same diagnosis code (DRG). Again, we do not find quantitatively meaningful pricing differences: on average, MA payments are 1.1 percent higher than TM payments. As we discuss below, this finding differs sharply from recent evidence on hospital payments in the under-65 market, where insurers frequently pay well above Medicare rates.

Geographic variation in TM spending has received a great deal of attention. It is often interpreted as a sign of regional differences in the efficiency of healthcare delivery within TM (e.g. Gawande 2009; Skinner 2011). We find that geographic variation in healthcare spending is around 20 percent higher in MA, whereas the geographic variation in hospital prices is about 20 percent lower.

We find suggestive evidence for some potential mechanisms by which MA insurers may reduce utilization relative to TM. The fact that spending per encounter is slightly higher in MA than TM is consistent with utilization constraints in MA, so that the marginal patient admitted for care is in worse health. We also find evidence of restrictions on the most expensive types of care, possibly including substitution to less expensive alternatives. MA patients are much less likely to be discharged from the hospital to post-acute care and much more likely to be discharged home than TM patients. Visits to specialists are much lower (22 percent) in MA than TM, while visits to primary care are only slightly lower (4 percent). Similarly, the probability of inpatient surgery is 7 percent lower in MA than TM while the probability of outpatient surgery is 26 percent higher.

The evidence on potential mechanisms helps alleviate – but does not remove – concerns that differences in average spending between MA and TM reflect differences in expected healthcare spending for individuals who select into MA, rather than a "treatment effect" of MA per se. Our baseline results compare spending in MA to spending in TM for individuals in the same county and with the same risk score. To the extent that county and risk score are the only variables that could be used in any capitation formula, this spending difference is a useful summary, which may provide a guide for, say, Medicare reimbursement rates. Yet, these differences in spending may partly (or entirely) reflect selection effects whereby MA attracts individuals with lower predicted spending, conditional on risk score and county.

In the final section of the paper, we therefore explore how estimates of mean spending differences between MA and TM are affected by more detailed controls for observable differences between TM and MA enrollees, as well as by attempts to adjust for unobserved differences between the two populations using data on mortality differences to proxy for differences in expected spending. Adjusting for county and risk score reduces the 30 percent raw spending difference between MA and TM to 25 percent. Finer controls for observables have little additional impact. Our attempts to use mortality differences to proxy for unobservable differences in expected TM spending between MA and TM enrollees yield a range of results; in our most aggressive adjustment, we find that spending differences between MA and TM enrollees shrink to 8 percent. While none of our approaches is perfect, we view the totality of the evidence as suggesting that MA reduces healthcare spending relative to what it would be in TM by 10 to 25 percent.

Our findings relate to several literatures. The most directly related are prior comparisons of healthcare spending in MA and TM, where as noted earlier, our key advance is access to detailed claims data for a large share of the MA market. Absent such data, prior studies have used a variety of approaches to infer healthcare utilization and spending differences between MA and TM. These include comparing MA plans' (mandatory) self reports of enrollee utilization to utilization measures in TM claims data (Landon et al. 2012), analyzing beneficiaries' self reports of care received in TM and in MA (Ayanian et al. 2013), analyzing hospital discharge data from New York counties experiencing MA exit (Duggan et al. 2015), and inferring cost differences from estimates of demand for MA and a supply-side model of the market (Curto et al. 2014). These papers have tended to find lower healthcare utilization in MA – with estimates ranging from 10 percent to 60 percent.

Our finding of similar pricing in MA and TM contrasts with the conventional wisdom that MA prices will be higher than TM prices due to the greater bargaining power enjoyed by the larger public sector (e.g. Philipson et al. 2010). It also differs from prior findings that TM prices are substantially lower than prices in the private, under-65 market both on the inpatient side (Cooper et al. 2015) and the outpatient side (Clemens and Gottlieb, forthcoming). This difference may be the consequence of regulation requiring hospitals to accept TM rates if they are not in the MA plan's network (Berenson et al. 2015).

Our findings of similar geographic variation in spending and pricing in MA and TM also contrast with recent findings that geographic variation in spending in commercial (i.e. under-65) insurance is similar to TM, but stems from much larger pricing variation and lower quantity variation in commercial insurance relative to TM (Philipson et al. 2010; Institute of Medicine 2013; Cooper et al. 2015). This contrast between TM and commercial insurance has been interpreted as reflecting the lower powered incentives in the public sector relative to the private sector in constraining utilization, and monopsony power in the public sector to constrain prices relative to what the private sector can achieve (Philipson et al. 2010). Of course, there are other reasons why patterns of healthcare provision for those under 65 may differ from the patterns for the over 65. We consider this same set of facts in the context of Medicare Advantage, which arguably provides a cleaner comparison group to TM for understanding variation under private and public regimes since MA and TM are provided to the same broad population.

Our finding that Medicare Advantage appears to reduce “high value” and “low value” care in similar measure contributes to what we believe is an emerging, cautionary tale on the bluntness of available instruments in the healthcare sector. Our evidence here speaks to the blunt nature of supply-side restrictions on care. Likewise, on the demand side, recent evidence suggests that high deductible plans reduce “high value” and “low value” care in equal measure (Brot-Goldberg et al. 2015), and that even targeted increases in the price of some types of care can depress care use across the board, including free preventive care services (Cabral and Cullen 2011).

Most broadly, our work is part of the large literature on the relative consequences of public and private ownership. This literature has spanned a range of disparate industries, including education, pensions, electricity, and transportation. In the specific context of healthcare, recent empirical work has emphasized that the private sector may be more efficient than the public sector at setting reimbursement prices for providers (Clemens et al. 2015) and at setting cost-sharing to combat moral hazard (Einav et al. 2016).

The rest of the paper proceeds as follows. Section 2 provides some institutional background on our setting. Section 3 describes our data and baseline sample. Section 4 presents summary statistics on healthcare spending in MA and introduces our baseline measurement approach for comparing spending in MA to spending for a “comparable” set of TM enrollees. Section 5 compares healthcare spending in MA and TM, overall and for various categories of people and spending. Section 6 examines differences between MA and TM enrollees in healthcare utilization and in healthcare prices, and examines some potential mechanisms for utilization reductions. Section 7 explores alternative approaches to controlling for selection into MA. The last section concludes.

2 Setting and background

The Medicare Advantage (MA) program allows Medicare beneficiaries to opt out of traditional fee-for-service Medicare coverage and enroll in private insurance plans. The program was established in the early 1980s with two goals: to expand the choices available to beneficiaries and to capture cost savings from managed care. In return for covering enrolled beneficiaries’ healthcare expenses, private MA plans receive a risk-adjusted, capitated monthly payment from the Centers for Medicare and Medicaid Services (CMS), which is the federal agency that manages the Medicare program.

There has historically been a tension between the two goals of expanding access to MA and limiting costs (McGuire, Newhouse, and Sinaiko 2011). Insurers have tended to participate more in periods with higher payments, and to offer more plans in areas with higher payments. MA plans also enroll relatively healthier beneficiaries, complicating the problem of setting appropriate capitation rates. Reforms over the last decade have aimed to address these problems by introducing a risk scoring system to adjust plan payments based on enrollee health, and a competitive bidding system that replaced the fixed reimbursement rates used earlier. These changes, combined with an increase in capitation rates set by CMS, have coincided with the expansion of plan offerings and enrollment seen in Figure 1. Enrollment in MA tends to be especially high in urban areas; in 2010, MA penetration was 33% in urban counties and 18% in rural counties.

To participate in MA, insurers must contract with a set of healthcare providers and offer at least the same insurance benefits as standard Medicare, which covers inpatient ("Part A") and outpatient ("Part B") healthcare services. MA plans typically provide additional benefits as well, in the form of more generous cost sharing or supplemental coverage of dental, vision, or drug benefits. Medicare beneficiaries observe the MA plan offerings in their county of residence and can choose to enroll in any of the available MA plans during an annual "open enrollment" period every fall. The trade-off they face in choosing between MA and TM is that MA plans typically restrict access to healthcare providers, but provide additional benefits as described above. In our data (before applying the sample restrictions described below), 73 percent of MA enrollees were in HMO or PPO plans with limited provider networks.

Every year, plans enter into a bidding process, which dictates the benefits and premium associated with each plan that is offered to beneficiaries The precise rules of the way plan bids translate to plan premiums and benefits are somewhat complicated. Curto et al. (2014) provide a detailed description; we briefly summarize the key features here. Each plan submits a bid b, which should be interpreted as the monthly compensation required by the plan to provide "standard" monthly coverage in the local area in which the plan is offered to an "average" Medicare beneficiary. By "standard" coverage we refer to the standard Part A and Part B financial coverage offered by TM; MA plans typically offer more comprehensive coverage, but they obtain a separate compensation from CMS for it on top of their bid b; this is known as the "rebate." As will be clearer later, by "average" beneficiary we refer to a beneficiary with an average health risk.

This bid b is then assessed against its local benchmark B, which is set administratively by CMS. In principle the benchmark B is supposed to approximate the counterfactual cost to CMS to cover an "average" beneficiary in that county through TM. In practice, the variation in benchmarks across locations departs somewhat from this principle, presumably reflecting various political economy considerations; on average in our observation period (2010), benchmark rates are higher than corresponding TM costs, and more so in some areas than in others.[1] Overall in our data (again, before applying the sample restrictions described below), the average benchmark across counties (weighted by the number of Medicare beneficiaries) is $836 per enrollee-month, compared to an average TM cost of $798, and this difference is lower in urban counties (benchmark of $866 and average TM costs of $842) than in rural counties ($770 vs. $716). However, in our observation period, the vast majority of plan bids are lower than the corresponding benchmarks, making MA plans financially more generous than traditional Medicare, where enrollees can face large out-of-pocket costs.[2]

Capitation payment to insurers for enrolling a given enrollee in a given MA plan depends

[1] Indeed, the 2010 Affordable Care Act reduces the level of these MA benchmark rates in subsequent years.

[2] If $b > B$ the difference is charged as a premium to the consumer. If $b < B$, which is almost always the case empirically, 75 percent of the difference is given to the consumer through the rebate, and 25 percent is retained by CMS.

not only on the plan's bid b but also on the enrollee's risk score r_i, which is proportional to her predicted healthcare costs in TM over the next year. Adjusting reimbursement for risk score is a key component of CMS's attempt to limit selection into MA by adjusting plan compensation for predictable heterogeneity in healthcare cost across beneficiaries. CMS assigns a risk score to each Medicare beneficiary based on demographic information and detailed claim-based information on chronic health conditions measured over the previous 12 months. The average beneficiary's risk score is normalized to 1, so that plans obtains compensation of $r_i b$ for covering beneficiary i. For purposes of setting MA plan payments, CMS deflates estimated risk scores for MA enrollees (by 3.41 percent in 2010, which is our sample year) to reflect CMS' estimate of the "upcoding" of risk scores for MA beneficiaries (CMS 2010; Geruso and Layton 2015).

Thus, broadly speaking, plan compensation is designed to reimburse an MA insurer for the costs an enrollee would incur – based on her county and risk score – had she remained in TM. This motivates our baseline approach (described below) of comparing utilization and healthcare spending in MA and TM, which is focused on comparing enrollees who are in the same county with the same risk score.

3 Data and sample construction

3.1 Data sources

This paper uses data from two main sources: the Health Care Cost Institute (HCCI) and the Center for Medicare and Medicaid Services (CMS). All the data pertain to spending and enrollment in 2010. Appendix A provides more details on the data and sample definition; Appendix B provides more details on the definition and construction of the specific healthcare spending and utilization variables we analyze.

The HCCI data are the key, novel data in this paper. HCCI is provided with claim-level data from three large MA insurers – UnitedHealthcare, Humana, and Aetna. HCCI pools these data (masking the individual insurers) and makes these data available for research. In 2010, these three insurers (hereafter referred to as the "HCCI insurers") covered almost 40 percent of MA enrollees: UnitedHealthcare was the largest (national market share of 18%), Humana was second (15%), and Aetna fifth (4%) (Kaiser Family Foundation, 2010). The claim-level data reflect claims that these three insurers paid out to healthcare providers. The HCCI data also contain monthly enrollment indicators and some limited enrollee demographics (age bins, gender, and zip code).

The CMS data serve multiple roles. One role is to provide parallel claim-level data for Medicare beneficiaries enrolled in Traditional Medicare (TM). Because TM offers fee-for service coverage, we essentially observe every healthcare claim made by TM enrollees during 2010. The TM claims data allow us to form a "benchmark" comparison of healthcare spending and utilization against which we can compare the measures obtained from HCCI.

The CMS data have a second, equally important role: providing enrollment, demographic, health and mortality data for all enrollees (TM and MA). For the universe of Medicare enrollees we can observe monthly enrollment information in TM (Parts A and/or B) or MA, risk score, demographics (zip code, age, and gender), dual eligibility status (in Medicaid and Medicare), detailed health conditions from the prior year, and mortality. The detailed CMS data on MA enrollees allow us to validate the completeness of our baseline sample in HCCI, and to adjust our comparison to TM spending for the differential demographics, health conditions, and mortality among MA enrollees compared to TM enrollees.

Finally, the CMS data contain detailed information on payments to MA insurers by CMS. This allows us to construct payments to MA plans per enrollee-month, as well as payment components.

3.2 Baseline sample

The HCCI data include most, but not all, MA enrollees in the three HCCI insurers. Based on the qualitative information that HCCI obtained from the three participating insurers, it appears that inclusion in the HCCI data was made on a plan-by-plan basis, with "highly capitated plans" left out. That is, insurance plans that pay providers on a capitated basis are omitted from the HCCI data. The HCCI data also indicate that they excludes special needs plans (SNPs), which are MA plans for individuals with specific diseases (such as end-stage liver disease, chronic heart failure, or HIV-AIDS) or certain characteristics (such as residence in a nursing home).

Ideally, we would have plan identifiers in the HCCI data, which would allow us to match this information to the plan identifiers in the CMS data, and thus know which MA plans are excluded. This would allow us to adjust for the demographics and health conditions of MA enrollees specifically enrolled in HCCI plans. However, with the exception of SNPs that are not in the HCCI data and can be identified in the CMS enrollment data, plan and insurer identifiers are omitted from the HCCI data. Instead, we rely on the fact that the MA market is localized and the use of provider capitation is most common in particular regions such as California, and construct our baseline sample by focusing on states where the HCCI data coverage appears to be approximately complete.

We judge the completeness of the HCCI data by comparing enrollment statistics for the HCCI insurers in the HCCI and CMS data. In the CMS data, we know for each MA enrollee whether he or she was enrolled in an MA plan offered by one of the HCCI insurers. This allows us to generate a pseudo HCCI enrollment data set in the CMS data, which covers all enrollees who "should" have been in the HCCI data if no plans were omitted. We then compare enrollee-month counts in this pseudo HCCI enrollment data and cross validate the actual HCCI data against it. Specifically, we compare enrollee-month counts at the state level across the two data sets, restricting the analysis to individuals who are 65 and over; we do not require individuals to be enrolled for a full year.

We define our baseline sample to be the set of 36 states where we have a close to complete sample of HCCI insurers' enrollees, which we define to mean that the count of enrollee-months in HCCI in the state is within 10 percent of the count for the HCCI insurers in the pseudo HCCI enrollment data. In practice, in these 36 complete data states, total HCCI enrollment is within one percent of total enrollment in the pseudo HCCI enrollment data, leaving us reasonably sanguine that we have captured the entire set of MA enrollees for these three insurers. Appendix Table A1 provides more details on state-by-state enrollee-month counts in the HCCI insurers as measured in the HCCI and CMS data.

The 36 states in our baseline sample represent about 60 percent of enrollees for the HCCI insurers. As shown in Appendix Figure A1, the excluded states are disproportionately concentrated in the Western United States. Appendix Table A1 shows the MA share of total Medicare enrollees and the HCCI insurer share of MA enrollees by state, including both the 36 complete data states and the 15 omitted states.

Table 1 shows how our baseline sample is constructed, and Panel A presents basic demographic statistics from both the CMS and HCCI data. Throughout the paper, risk scores for TM enrollees are unadjusted, while risk scores for MA enrollees are adjusted to reflect the 3.41% deflation CMS applies in determining MA payments, as described above and in CMS (2010, page 19).

Columns (1) through (3) present CMS data across all plans and states, while columns (4) through (6) present CMS data for our baseline sample, which is comprised of the 36 states above and omits enrollees in SNPs. In each case, we present statistics for all TM enrollees, for all MA enrollees, and then for enrollees in the three HCCI insurers. Columns (7) and (8) present statistics for the HCCI data, for the entire sample in column (7) and for our baseline sample in column (8).

We use Table 1 to make several observations. First, comparing columns (1)-(3) to columns (4)-(6), the 36 states that constitute the baseline sample do not seem to be very different from the overall sample, making us feel reasonably comfortable that the findings we report throughout the paper are likely to be relevant for states not covered by our baseline sample. Second, comparing column (2) to (3) or column (5) to (6), it appears that the three HCCI insurers attract enrollees that seem reasonably similar to the overall MA enrollees, suggesting that our subsequent findings may apply to the broader MA population. Third, as has been documented elsewhere, MA enrollees are slightly younger and significantly healthier than TM enrollees: their risk scores (which are proportional to their predicted healthcare spending) are about 5-10 percent lower, and their annual mortality rates are almost a third lower. This suggests that a straight comparison of TM and MA healthcare spending would be misleading, motivating the various corrections for selection we describe in the next section.

Finally, it is reassuring that, for our baseline sample, the enrollment counts and demographics (that we can measure in both data sets) are remarkably similar when measured in the pseudo HCCI enrollment data set we construct in the CMS data (column (6)) and the actual HCCI data (column (8)). This is what we would expect given our construction of a baseline sample for which the HCCI data should include all relevant MA enrollees.[3]

[3] We have about 1 percent more enrollees in our HCCI sample (column (8)) than the pseudo-HCCI sample in the CMS data (column (6)). This is to be expected, given that plan assignment is missing for about 1 percent of MA enrollees in the CMS data.

4 Summary statistics and measurement approach

4.1 Spending and payments in MA

Table 1 Panel B reports average total healthcare spending and CMS payments in TM and MA. Throughout, we define healthcare spending as the sum of insurer spending and any out-of-pocket spending by the beneficiary. Insurer spending is based on observed payment amounts – that is, transacted prices, not list prices. Out-of-pocket spending is the amount owed by the enrollee (due to deductibles and co-insurance).[4]

Our measure of total spending is a near-exhaustive measure of all healthcare claims. Specifically it covers several categories of spending: (a) inpatient spending, which is associated with providers identified as hospitals and physicians billing for treatment provided in an inpatient hospital setting; (b) outpatient spending, which also includes home health care and durable medical equipment (e.g. wheelchair rentals); and (c) skilled nursing facility (SNF) spending.[5] Average MA healthcare spending per enrollee-month is $642 in our baseline sample (column (8)). Of this, $590 is paid by the insurer, and $52 is owed by the enrollee.

Table 1 Panel C reports mean payments to MA insurers. Payments to MA insurers for "organic" MA services (i.e. for services that would be covered by TM) are $767 per enrollee-month in our baseline sample (column (6)).[6] The comparison of insurer MA revenue of $767 per enrollee-month to the insurer payments to healthcare providers of $590 suggests that net revenues for MA insurers are $177 per enrollee-month, or about 30 percent above MA insurer healthcare spending. If this applied to the entire MA population in 2010 (including those outside our sample) it would imply $21 billion in annual (2010) revenue for MA insurers in excess of their spending on healthcare claims. Of course, MA insurers incur additional costs, such as administrative and advertising expenses, which we do not observe in our data.

[4] TM enrollees can purchase supplemental private insurance ("Medigap" or employer sponsored) to cover some or all of their out-of-pocket expenses. About half do so. If they do, the suplemental insurer is the primary payer of the "out-of-pocket" amount owed by the beneficiary.

[5] One (small) category of spending that is not in our measure of total spending is hospice care. This is because hospice care is billed directly to CMS even for MA enrollees, so it is observed in CMS data, for both TM and MA and doesn't fully conform to the empirical exercise. In practice, we show below that the exclusion of hospice spending does not substantively affect the comparison of total spending.

[6] We define payments to MA insurers to be the sum of CMS spending on MA ($778) and additional consumer premiums for MA ($6) minus the portion of the consumer rebate that is passed on to consumers for additional services, not covered by Medicare Part A and Part B services ($17). As discussed in Section 2, MA insurers typically offer more comprehensive coverage than TM, but they obtain a separate compensation from CMS for it, on top of their bid. On average in our baseline sample, the consumer rebate is $51 per enrollee-month, and $34 of it is for more generous coverage of the healthcare services that would be covered by TM and that we study in the paper, while the remaining $17 of the rebate is for additional consumer benefits that are not captured by the analogous TM spending (such as premium discounts, or dental and vision coverage).

4.2 Spending in MA and TM: raw comparisons

Table 1 Panel B reveals dramatic differences in total healthcare spending between the TM and MA populations. In our baseline sample, the average TM enrollee spends \$911 per month (column (4)), while the average MA enrollee spends 30% less, \$642 (column (8)).

Figure 2 shows raw spending in MA and TM separately for each of the 36 states in our baseline sample. Spending is lower in MA in all states, but the differences range from about 3 percent lower MA spending in Alaska to over 45 percent lower MA spending in Florida and Vermont.

Geographic variation in spending within TM has attracted a great deal of attention. The "Dartmouth Atlas" findings of large differences across areas in TM spending and utilization without corresponding differences in mortality is widely viewed as indicative of the inefficiencies of the public Medicare system (Fisher et al. 2003a, 2003b; Skinner 2011; Institute of Medicine 2013). Our analysis suggests that, if anything, geographic variation in raw spending is higher in MA than TM. The coefficient of variation across states (weighting each state by its total Medicare enrollment) is 0.136 in MA, about 20 percent higher than the 0.114 coefficient of variation we estimate in TM.[7] In Appendix Figure A2 we show that MA also exhibits the positive correlation across states between spending and mortality that has been widely documented in TM.

4.3 Measurement

Lower baseline spending in MA relative to TM may partly or entirely reflect differences in the beneficiaries who enroll in TM and MA. We have already seen in Table 1 that MA enrollees tend to be healthier than TM enrollees. This motivates our baseline empirical strategy in which we reweight the TM population to match the MA population in terms of county and risk score. The risk score is a summary statistic based on an extremely rich set of demographic and health measures. These health measures reflect both patient health and propensity to receive healthcare – since diagnoses are only recorded if care is received (Song et al. 2010; Finkelstein et al. 2016) – both of which may differ between TM and MA enrollees.

Specifically, consider a Medicare enrollee in county z_i with (continuous) risk score r_i, and an outcome y_i^{TM} in TM. We map r_i to a discrete risk score bin r_i', so that all Medicare beneficiaries are partitioned into a set of discrete groups, defined by their county and risk score bin $g_i = (z_i, r_i')$. Using the sample of beneficiaries in the CMS data who are enrolled with the HCCI insurers (Table 1, column (6)), we assign each group g a weight $w_g = N_g/N$, where N_g is the number of enrollees

[7] Our analysis is at the state level rather than the Hospital Referral Region (HRR) level that is more typical in this literature. This is because many HRRs cross state boundaries and our baseline sample is limited to a subset of states.

that belong to group g and $N = \sum_g N_g$.[8] Each unweighted TM outcome

$$\overline{y}^{TM}_{unweighted} = \frac{1}{N_{TM}} \sum\nolimits_{i \in TM} y_i^{TM} \tag{1}$$

is then replaced with a reweighted TM outcome

$$\overline{y}^{TM}_{re-weighted} = \frac{1}{\sum_{i \in TM} w_{g_i}} \sum\nolimits_{i \in TM} w_{g_i} y_i, \tag{2}$$

which we compare to the corresponding MA outcome

$$\overline{y}^{MA} = \frac{1}{N_{MA}} \sum\nolimits_{i \in MA} y_i^{MA}. \tag{3}$$

In addition to the transparency and simplicity of this re-weighting approach, it has the added attraction that it captures the spirit by which MA insurers are being paid by CMS. As described in Section 2, CMS payments to MA insurers are based on a county-specific benchmark, and multiplied by the enrollee's risk score r_i. Our baseline approach, which reweights on precisely these two dimensions – county and risk score – can therefore be viewed as correcting for selection concerns associated with the two dimensions on which CMS varies its payments. As mentioned above, following CMS's payment policy for MA insurers during our 2010 study year, we use risk scores for MA enrollees that are deflated by 3.41%.

Naturally, there may still be selection into MA on characteristics which, conditional on risk score and county, are correlated with expected healthcare spending. In Section 7 we return to this issue, and report several alternative strategies for adjusting for selection into MA using both a richer set of observables (implemented via propensity-score matching) and an attempt to account for selection on unobservables using observed mortality differences between MA and TM enrollees. As we show there, while various approaches to selection move some of the numbers around, the qualitative and the ballpark quantitative conclusions do not change dramatically in most specifications relative to our baseline approach. This makes us comfortable "riding" this relatively simple baseline approach for much of the paper.

Table 2 shows how the TM spending benchmark is affected by different ways of reweighting the TM enrollees to "look like" the MA enrollees in terms of county composition and risk score. Column (1) reproduces the raw, unweighted numbers already shown in column (4) of Table 1. Column (2) of Table 2 reweights the TM data to match the distribution of MA enrollees across counties. Average TM spending per enrollee-month increases from \$911 to \$942, reflecting the fact that MA enrollees are disproportionately in more expensive counties; this is primarily driven by the well-documented higher MA penetration in urban areas, in which healthcare delivery tends to

[8] A slight complication of this procedure arises when an MA enrollee belongs to a group for which there are no TM enrollees, which may happen in small counties and high (i.e. less common) risk scores. This applies to only 0.07 percent of enrollee-months. In such a case, we amend this procedure with an extra step, where we re-classify to such "empty" TM groups the TM enrollee in the same county whose risk score is the closest to the corresponding unmatched MA enrollee.

be more expensive. Columns (3) and (4) add risk scores to the reweighting of the TM population, so that it matches, county by county, the risk score distribution of MA enrollees. In column (3) we match on risk score bins that are quite coarse, of width 0.5; 58% of MA enrollees are in the three largest bins (0.5-1, 1-1.5, and 1.5-2). In column (4) we use more granular risk score bins (of width 0.1). It is evident from column (3) (and not surprising given Table 1) that reweighting on risk scores is important, reducing the average monthly spending by 9% relative to reweighting on county only in column (2). However, it is quite remarkable that the much more granular matching on the risk score distribution makes little difference, with columns (3) and (4) showing essentially identical results.

Going forward, we will use the re-weighting strategy in column (4) – using county and risk bins of width 0.1 – as our baseline when reporting mean spending or quantity differences between MA and TM. We will show both unweighted and reweighted statistics throughout the paper, but will concentrate our discussion on the reweighted statistics, unless we explicitly note otherwise.

5 Differences in spending in MA and TM

Overall differences Table 2 shows average spending differences across all our baseline sample enrollees in MA (column (5)) and comparison samples in TM. The unweighted data indicate that healthcare spending in MA is \$269 (30%) lower per enrollee-month than in TM. Using our baseline re-weighting strategy (column (4)), we estimate that healthcare spending by MA enrollees is \$213 (25%) lower per enrollee-month than a comparable (on county and risk score) sample of TM enrollees.

Stated differently, in the spirit of CMS' capitation payment formula, if total healthcare spending of MA enrollees under TM were the same as for TM enrollees with the same risk scores in the same counties, they would cost \$855 per enrollee-month, while in MA their total healthcare spending is only \$642. Applying this estimate to the entire MA population in 2010 (column (2) of Table 1, which includes those outside of our baseline sample), this translates to \$101.5 billion in annual (2010) healthcare spending in TM relative to \$76.3 billion in healthcare spending in MA, a difference of \$25.2 billion in annual healthcare spending.

Differences by consumer type Panel A of Table 3 reports the spending differences for different types of enrollees. Each row represents a different subsample of enrollees. Across the board, overall spending in MA is always significantly lower than the (re-weighted) TM analog; the average difference reported in Table 2 is not driven by any specific sub-population. Yet, we see some heterogeneous effects across types of enrollees. The difference is higher in both absolute and relative terms for elderly beneficiaries; the youngest Medicare beneficiaries (aged 65-74) are associated with lower MA spending of \$120 per month (18%) while the most senior (85 years old and over) are associated with a difference of \$378 (30%) per month. Looking at beneficiary location, the spending difference is much greater for urban counties, which is where the vast majority (77%)

of MA beneficiaries enroll. In urban counties, MA spending is 27% lower than TM spending, while in rural counties it is only 16% lower. Put differently, average spending per month in MA is almost the same for rural and urban counties, but TM spending is much higher in urban counties, thus generating the differential difference. This sharp difference between urban and rural counties is also reflected in the MA revenues (i.e. in plan payments for "organic" MA services from Table 1 Panel C), which we estimate to be $205 higher than claims cost in urban counties and only $83 higher in rural ones.

Panel A also reveals an interesting aspect of the role that the reweighting adjustment plays. A comparison of columns (2) and (3) reveals that reweighting does not reduce the monthly TM spending estimates uniformly across different sub-populations. Using beneficiary age to illustrate, we note that the re-weighting adjustment makes almost no difference for the most senior (85 and older) – essentially suggesting that there is little systematic selection on county and risk scores for this subgroup (or that if there is, it cancels out) – but makes a larger difference for younger beneficiaries.

Panel B of Table 3 compares different quantiles of the MA and TM spending distributions. This allows us to assess whether the spending difference is driven, for example, by the highest spenders. Again, we see the overall lower MA spending across all parts of the distribution. We see a larger percentage difference at the lowest end, a fairly stable (and sizeable, of about 30%) difference throughout much of the distribution, and then a somewhat lower percentage difference at the very top one or two percentiles.

Figure 3 shows that states with higher TM spending have greater MA "savings" as measured by the percentage difference between MA spending and adjusted (i.e. re-weighted on risk score and county) TM spending. This is consistent with the "conventional wisdom" that higher spending TM areas are less efficient or productive (e.g. Skinner 2011).

Differences by spending type Table 4 looks at spending differences across different categories of care. It shows total spending broken down into three mutually exclusive and exhaustive categories: inpatient, outpatient, and SNF. MA spending is lower in all three categories. It is 19% lower for inpatient and 25% lower for outpatient. There is a much larger difference in SNF spending, where MA spending is almost 50% lower than in TM. However, SNF spending accounts for only a small share (11%) of overall spending, so this large percentage difference does not contribute much to the overall difference in spending.[9] We return to the SNF results when we discuss potential

[9] The Institute of Medicine (2013) recently called attention to the fact that variation in post-acute spending is a major driver of geographic variation in TM spending. This appears to be true in MA as well, where the geographic variation in SNF spending is even larger (relative to other types of spending) than in TM. For example, compared to the coefficient of variation across states of 0.11 in overall (unadjusted) TM spending and 0.14 in overall MA spending (see Figure 2), we estimate a coefficient of variation in SNF (unadjusted) TM spending of 0.19, and 0.33 in SNF MA spending. By contrast, relative geographic variation in inpatient and outpatient spending in TM and MA is similar to the overall comparison (not shown).

mechanisms for reducing healthcare use in Section 6.4 below.

The bottom row of Table 4 reports hospice spending in MA and TM. As noted earlier, hospice is covered by TM for both MA and TM enrollees. It is therefore not in our HCCI data on MA spending and we do not include it in our baseline "total spending" measure. It is however captured – for both MA and TM enrollees – in the CMS data. We therefore use the CMS data to measure hospice spending for both TM enrollees and enrollees in the three HCCI insurers. Because MA insurers do not bear the cost of hospice expenditures, they might have an incentive to steer patients to hospice, so that some of the lower MA spending in inpatient, outpatient, and SNF could be offset by higher spending in hospice. The bottom row of Table 4 suggests, however, that this is not the case. Hospice spending is too low to have any potential significant offset effect; moreover, it is also lower (rather than higher) for MA enrollees than for TM enrollees.

6 Differences in utilization, not in prices

We examine whether the substantial (25%) difference in overall healthcare spending per enrollee-month between MA and TM is driven by lower healthcare utilization in MA or by the ability of MA insurers (at least the large ones, from which we have data) to negotiate lower prices, or both. One challenge throughout this section is to conceptually separate prices from quantity or quality of care, and this challenge dictates some of the exercises we report. To preview our results, we find that quantity differences appear responsible for the entire difference; various measures of "prices" are all quite similar in MA and TM.

6.1 Differences in the propensity of healthcare encounters

Table 5 compares components of healthcare utilization. We examine inpatient days and admissions, days in skilled nursing facilities (SNFs), visits to the emergency department (ED), and physician visits. Across all categories, utilization in MA is substantially lower.

Inpatient days are 21 percent lower, and SNF days are 56 percent lower. These differences in days are quite similar to the differences in inpatient spending (of 19 percent) and SNF spending (of 48 percent) shown earlier in Table 4. Conditional on an inpatient admission, length of stay is also slightly (6%) lower in MA.

ED visits are 16 percent lower in MA. This reflects lower utilization both for outpatient ED visits (ED visits that do not result in an inpatient admission) and inpatient ED visits (which do result in an inpatient admission).

Physician visits in an outpatient setting are similarly – 17 percent – lower. This difference is approximately equally driven by the extensive and intensive margin: a 10% lower rate of MA enrollees who see a physician at least once during the month and an 8% lower average number of physician visits by MA enrollees who visit the physician at least once.

Over-used and under-used care In Table 6 we explore differences in potential low-value and high-value care. Panel A examines utilization of diagnostic testing and imaging services, where excessive use may be a concern (e.g. Brot-Goldberg et al. 2015; U.S. Government Accountability Office 2008). Panel B examines utilization of various measures of preventive care, an area where under-use may be a concern (Brot-Goldberg et al. 2015).[10]

We see lower utilization in MA for both low-value and high-value care. Diagnostic tests and imaging procedures are, respectively, 24% and 19% lower in MA, which is similar to, and not higher than, the percentage difference in total spending. Preventive care also exhibits no obvious pattern relative to overall care; rates of most preventive care are lower in MA, although there is variation across the measures. Flu shot rates for MA beneficiaries are much lower (by 38%). Most other preventive tests are also lower in MA but the differences are smaller. Interestingly, the one area where screening tests are done more frequently in MA than in TM is screening tests that are female-specific (mammograms and pap smears), for which the rates are a little higher in MA.

In Panel C we use a widely-used algorithm developed by Billings et al. (2000) to classify ED visits by their "appropriateness." The algorithm uses primary diagnosis codes for the visit to distinguish between visits that represent an emergency (i.e. require care within 12 hours) and non-emergency visits (e.g. a toothache). Within emergency visits, it further distinguishes between those that require treatment in the ED (as opposed to being treatable in a primary care setting, such as a lumbar sprain). Finally, within emergency visits that require ED care, it distinguishes between those that were and were not preventable by timely ambulatory care. Appendix B provides more detail on the algorithm and its validation.

The results indicate similar proportional reductions in each type of ED visit, irrespective of its "appropriateness." Emergency visits are 16% lower, while non-emergency visits are 15% lower. Within emergency visits, those that require ED care are 17% lower while those that were primary care treatable are 16% lower.

Overall these results suggests that Medicare Advantage is a relatively blunt instrument for reducing health care utilization, with "high value" and "low value" care showing similar proportional differences to TM. Interestingly, the bluntness of supply-side instruments such as managed care is mirrored on the demand side, where recent work suggests that high deductible health insurance plans are similarly non-discriminatory in discouraging both high-value and low-value care utilization (Brot-Goldberg et al. 2015) and Medicaid coverage for the previously-insured encourages increases in ED visits of all types, including (and perhaps particularly) non-emergency visits (Taubman et al. 2014).

[10] We show rates of preventive care by enrollee-month to be consistent with the analysis in the rest of the paper. Naturally, recommended care is not at a monthly level but typically at an annual (or bi-annual) level. The analysis looks similar if instead we examine these measures on an annual basis (not shown).

6.2 Similar spending per encounter

Table 7 shows spending per encounter in MA and TM. Given the close similarity between the percentage difference in utilization measures in Table 5 and the percentage difference in the corresponding spending measure in Table 4, it is not surprising that spending per encounter is quite similar between MA and TM. Inpatient spending per admission, inpatient spending per day and SNF spending per SNF day are essentially the same in MA and TM. Interestingly, spending per outpatient ED visit is 9 percent higher in MA; this may reflect utilization management for MA patients that discourages relatively less severe cases from coming to the ED or from being admitted from the ED to the hospital. We also note that the reweighting approach makes little difference for inpatient spending; the spending per encounter statistics are quite similar already in the raw comparison of means.

In the last two rows of Table 7, we briefly consider a specific case study: spending per inpatient admission for AMIs (acute myocardial infarction, or heart attack). Focusing on spending per admission for a particular diagnosis allows us to get closer to a pure price comparison. The choice of AMI is motivated by the attention it has previously received in the literature; this in part stems from the general sense that differential selection into the hospital may be less of a concern for this type of acute, emergency event than for other, more discretionary admissions. Indeed, Cutler et al. (2000) famously compared treatment for heart attack patients in *private* managed care (HMO plans) and *private* FFS plans in Massachusetts under the assumption that while patients may select plans based on their expected incidence of disease, conditional on the event occurring there should be minimal differences across plans in the severity of the disease.

We find that spending per AMI admission or AMI day is quite similar in MA and TM. Specifically, we estimate that spending per AMI admission is about 1 percent higher in MA, and spending per day is about 3 percent lower.[11] Our finding of similar spending per AMI admission in private managed care and public FFS care stands in marked contrast to Cutler et al. (2000)'s finding that spending per AMI episode was about 30 to 40 percent lower in *private* managed care (HMO plans) than in *private* FFS plans in Massachusetts.

6.3 (Lack of) Mean price differences for hospital admissions for specific diagnoses

Table 7 shows similar spending per encounter for MA and TM enrollees, suggesting that prices may be similar in MA and TM. However, spending per encounter can also be affected by differences in providers seen or in reason for the visit; one motivation for our AMI "case study" is to try to look within a single reason for admission.

[11] This analysis of spending per admission for a given condition is similar in spirit to Baker et al.'s (2016) analysis of spending per admission for a common basket of DRGs and geographic areas. They also use HCCI data (from 2009 and 2012) and, focusing on large DRGs and large metropolitan areas, conclude that MA spending per admission is 8 percent lower than TM spending for the same "basket" of DRGs and areas.

To hone in on differences in "prices" – or unit payment rates – we compare payments in MA and TM for admission to the *same* hospital with the *same* DRG.[12] Under TM, hospitals are paid by CMS based on a pre-set formula that is a product of a hospital-specific rate and a DRG-specific rate; it is our understanding (although no contractual data is available to verify it) that these hospitals are predominantly paid by MA insurers in a similar way. In TM, and presumably in MA as well, some accommodation for exceptions is allowed, resulting in payments that may deviate from the DRG-hospital formula rates.

We compute a parallel set of prices in MA and TM. For both, our starting unit of analysis is an admission in MA, which is characterized by a hospital and a DRG. The MA price is simply the observed (transacted) payments for the admission in the MA claims data. Construction of the TM price proceeds in two steps. First, for each MA admission, we calculate the formula price in TM, applying the PPS reimbursement formula which, as noted, is a function of the hospital and the DRG. Second, we adjust our TM formula prices to reflect average differences between TM formula and TM actual (transacted) prices since we are comparing to actual (transacted) prices in MA.[13] Appendix C provides more detail.

Figure 4 shows our estimate of the average price in TM and MA overall, and for the top 20 DRGs (by their share of MA admissions); Appendix Table A2 provides the underlying numbers. In reporting DRG-specific average prices, we weight the admissions in each DRG by the state's share of MA admissions in all DRGs, so that any differences in average prices across DRGs within MA (or within TM) reflect price differences for a common "state basket," and are not contaminated by differences in the geographic distribution of admissions by DRG across states. The national average price is computed by weighting each DRG by its (national) share of MA admissions.

Inpatient prices are extremely similar in MA and TM. The national average admission price is \$9,945 in TM and \$10,054 in MA. The price for an average MA admission is only 1.1 percent higher in MA relative to TM. The largest difference among the top 20 DRGs is for chest pain (DRG #313), for which the average MA price is about 6% lower than in TM. For 10 of the top 20 DRGs, the average price in MA is within 2 percent of that in TM.

The close similarity of inpatient admission prices between MA and TM is interesting given that

[12] For this pricing analysis, we focus on the approximately 4,000 hospitals in our baseline sample that are paid (by TM) under Medicare's prospective payment system (PPS). These represent about 95 percent of all inpatient admissions in MA and cover essentially all standard (non-specialty) hospitals.

[13] In principle, we could follow the exact same approach as for MA prices, and estimate transacted TM prices directly in the CMS data, where we observe TM payments for each admission, along with its hospital and DRG. In practice, however, we are constrained from doing this for two reasons: hospital identifiers are encrypted in the MA data, and our DUAs prohibit our exporting data below a minimum cell size. Fortunately, the TM hospital-specific base payment rates (which determine the TM formula payments) are available in our MA data; we are extremely grateful to Zack Cooper for providing us with this mapping. We construct actual and formula TM prices in the CMS data and use these to construct adjustment factors to reflect average differences between TM formula and actual prices by DRG or by state.

it is frequently conjectured that because the public sector has greater bargaining power, public fee-for-service may achieve lower prices than private insurance (e.g. Philipson et al. 2010). Consistent with this conjecture, prior empirical work has shown that for the same service, TM tends to reimburse at substantially lower prices than commercial (under 65) private insurance both in the outpatient setting (Clemens and Gottlieb, forthcoming) and the inpatient setting (Cooper et al. 2015). In contrast, we do not find that TM prices are substantially lower than MA prices.[14] One potential explanation for this discrepancy is that Medicare Advantage plans may have more bargaining power with hospitals than commercial plans since hospitals must accept fee-for-service Medicare rates when they are not included in the MA plan's network (Berenson et al. 2015).

Geographic variation in hospital prices We also compare geographic variation in inpatient prices for MA and TM. We construct average state prices in MA and TM following a parallel process to what we did for measuring DRG prices; now, we weight the admissions in each state using the DRG's national share of MA admissions, so that comparisons of state-level average prices within MA (or within TM) are not contaminated by differences in the mix of DRGs across states.

Figure 5 shows the results; Appendix Table A3 shows the underlying numbers. Pricing variation across states (weighted by Medicare enrollment) is about 20 percent lower in MA than in TM. Specifically, the coefficient of variation across states is 0.067 in MA, compared to 0.082 in TM. By contrast, recent work has shown evidence of substantially higher geographic pricing variation in commercial (less than 65) private plans compared to TM (Philipson et al. 2010, Institute of Medicine 2013, Cooper et al. 2015).[15]

6.4 Potential channels for saving

Our results thus far strongly point to differences in utilization metrics, rather than payment rates, that are driving the overall differences in spending between TM and MA. Potential mechanisms by which MA plans may reduce care utilization include: limited provider networks through which beneficiaries receive care, coordination of care programs to more efficiently deliver appropriate services and avoid excessive utilization, and financial incentives to physicians to influence the quality

[14] Of course, our MA sample is limited to three large insurers, and their bargaining power may not be representative of smaller MA insurers; on the other hand, Cooper et al. (2015)'s analysis of commercial pricing was also limited to the same three large insurers, and there average inpatient prices were almost twice as high as in TM.

[15] Like us, this analysis focuses on pricing variation in hospitals. The recent Cooper et al. (2015) comparison of pricing variation in TM compared to commerical (i.e. private, under 65) plans also uses data from HCCI, specifically 2007-2011 data for commercial insurance. We confirmed that we replicate their finding of substantially greater variation in pricing in commercial insurance relative to TM when, as with our main analysis here, we use data only from 2010 and from the subset of 36 states in our baseline analysis. Specifically, using the MA share of admissions in each DRG to construct average prices for each state, and estimating the coefficient of variation across states weighting each state by the Medicare enrollment in that state (as in Figure 5), we estimate that pricing variation is over 50 percent larger in commercial insurance (coefficient of variation = 0.14) than in TM (coefficient of variation = 0.08).

and quantity of services delivered (e.g. Landon et al. 2012). By contrast, in TM there are virtually no restrictions on physician clinical decisions or patient choices of care.

We have already seen evidence of one "signature" of MA mechanisms to reduce care utilization: all these mechanisms should constrain patient entry into care, particularly expensive care, so that the average person using that care in MA is in worse health, and is higher cost than the average person using that care in TM. In other words, MA enrollees should have fewer encounters, but have greater spending (or utilization) per encounter. Consistent with this, we found that spending per inpatient day and spending per outpatient ED visit were in fact slightly higher in MA than in TM (see Table 7).

In Table 8 we provide additional evidence consistent with restrictions on utilization. In Panel A we explore differences between TM and MA in the distribution of discharge destinations of hospitalized patients. Destinations are roughly ordered in how expensive they are (from cheaper to more expensive). The number of enrollee-months sent to different destinations is uniformly lower in MA, reflecting the lower total number of inpatient admissions in MA (see Table 5). However, inpatients covered by MA are disproportionately discharged to less expensive destinations. Discharges of MA enrollees directly to home are only 10% lower than in TM, discharges to a home health organization are 23% lower, and discharges to SNF are 38% lower; together, these three destinations make up about 85 percent of discharges in either TM or MA. Discharges to other post acute institutions (such as long-term care hospitals, cancer centers, or psychiatric hospitals) are less common, but significantly more expensive; they are 71% lower in MA than in TM.

In addition to limiting use of care, MA may also constrain the type of service, encouraging use of less expensive substitutes. Panel B points to some patterns that are suggestive of such channels. First, we analyze the frequency of surgeries. We find the surgery rate to be in fact higher, not lower, in MA by a fair amount (18%). However, inpatient surgeries are lower (by 7%) and outpatient surgeries are much higher (by 26%), which is suggestive of MA insurers using outpatient surgeries to substitute away from inpatient surgeries and perhaps (given the fact that overall number of surgeries is higher) from other types of expensive, non-surgical admissions as well. Second, we examine two types of physician visits: primary care and specialist visits. We already saw in Table 5 that MA enrollees are associated with 17% fewer physician visits. While, consequently, both types of physician visits are lower in MA, the percentage difference in the number of specialist visits is much greater. Primary care visits are only 4% lower, while visits to specialists are 22% lower.

7 Alternative approaches to correct for selection

The results thus far suggest that spending in MA is 25% lower than in TM, even after adjusting for county and a detailed measure of predicted health spending (risk score). To the extent that county and risk scores are the only variables that could be used in any capitation formula, this difference is a useful summary, which may provide a guide for, say, CMS reimbursement rates.

Nonetheless, we would like to know the extent to which this lower spending reflects a treatment effect of MA as opposed to selection into MA by individuals who – conditional on risk score and county – have lower predicted spending due to unmeasured differences in health or preferences for healthcare. The relative importance of selection or treatment is particularly important in the context of assessing the cost implications of any expansion of the MA program to cover those currently enrolled in TM.

We take several steps in this section to try to make progress on this question. We begin by showing that our baseline comparison of mean MA and TM spending is not sensitive to alternative, richer ways of controlling for observables. We then consider the possibility of selection on unobservables by using differential mortality rates (conditional on observables) in MA and TM to proxy for unobservable spending differences. This approach yields varying results, with the most aggressive adjustment suggesting that MA spending is only 8 percent lower than what it would be under TM.

The rest of this section discusses the implementation and results in detail. We emphasize at the outset that we consider these alternative approaches useful but clearly not a panacea for concerns about selection. Our earlier evidence pointing to potential channels by which MA may reduce spending – such as via substitution from inpatient to outpatient surgery or from specialist care to primary care – complements our empirical exercise here in suggesting the existence of an MA treatment effect. One would need a more subtle selection story, which moves beyond selection into MA on predicted spending, to explain these patterns. The same is true for many of our other results, such as the comparison of geographic variation. Overall, we view the results as pointing to a large "treatment effect" of MA on spending, in the range of 10 to 25 percent.

7.1 (Standard) framework

A standard potential outcome framework is useful to organize our exercise. Let $W_i = 1$ if beneficiary i is enrolled in a plan offered by one of the three HCCI insurers in MA, and $W_i = 0$ if i is in TM. Let y_i^{TM} be the individual outcome of interest (e.g. healthcare spending per month, which is the focus of this section) if she were in TM, and y_i^{MA} be the individual outcome of interest if she were in MA. We observe $y_i = y_i^{TM}$ when $W_i = 0$, and we observe $y_i = y_i^{MA}$ when $W_i = 1$. The individual treatment effect is $\Delta y_i = y_i^{MA} - y_i^{TM}$.

We observe (e.g. in Table 1 Panel B)

$$D = E\left[y_i^{MA}|W_i = 1\right] - E\left[y_i^{TM}|W_i = 0\right] = T + S, \tag{4}$$

where T is the average treatment effect for the MA population

$$T = E\left[y_i^{MA} - y_i^{TM}|W_i = 1\right] \tag{5}$$

and S represents the selection effect, given by

$$S \equiv E\left[y_i^{TM}|W_i = 1\right] - E\left[y_i^{TM}|W_i = 0\right]. \tag{6}$$

A key advantage – in the context of our data – of the above representation of the selection effect is that it is only a function of y_i^{TM}; this is attractive because the set of observables is significantly richer and more granular in the CMS data than in the HCCI data, and the above representation allows us to analyze the selection effect using CMS data alone, holding the average outcome of interest fixed in the HCCI data.

7.2 Correcting for selection on observables

Our baseline re-weighting approach (see equation (2)) can be viewed within this framework as assuming that, conditional on county and risk score, W_i is as good as random assignment. The risk score itself is generated from an underlying much richer set of observables, including very detailed health measures as well as age, gender, and dual eligibility in Medicaid. These observables are used with a particular functional form to produce the risk score. A more flexible approach therefore would be to condition on the individual components of the risk score.

If we want to condition on a richer set of observables, it gets more difficult to apply our baseline re-weighting strategy as the data become sparse and it becomes common to observe MA beneficiaries with a vector of characteristics for which there is no match in the TM sample. We therefore instead follow a standard approach of constructing propensity scores for enrollment in MA as a function of a rich set of observables, and then apply the reweighting strategy to the propensity score rather than to the entire vector of observables.

Specifically, given a vector of observables x_i we estimate a logit model of W_i on x_i. That is, we assume that $p_i = \Pr(W_i = 1) = \frac{\exp(x_i'\beta)}{1+\exp(x_i'\beta)}$ and estimate β by maximum likelihood. We estimate the logit model separately for each county, to allow the relationship between enrollment in MA and observables to differ across counties. We then use our estimate of β to generate the propensity score for individual i, denoted by $\widehat{p_i}$. Appendix Figure A3 shows the distribution of propensity scores under MA and TM for our baseline x_i's (county and risk score).

We then apply the same reweighting procedure used earlier, in two ways. First, we simply reweight the TM sample to match the propensity score distribution of the MA sample by binning the propensity score to bins of size 0.01. Second, because we think that location heterogeneity may be particularly important for healthcare spending, we also reweight on county and propensity score, so that reweighting groups are defined as a combination of county and a 0.01 bin of propensity score. Table 9 reports the results from both procedures, in columns (3) and (4), respectively, but it turns out that the additional conditioning on county in the reweighting procedure makes little difference, presumably because all our specifications already include county-specific estimates in the construction of the propensity score.

Rows 1 and 2 of Table 9 report the TM average spending when we apply no weights (row 1) and when we reweight on risk score (row 2), as in the baseline specification, regenerating the results from Table 2.[16] Rows 3 through 6 report specifications based on the propensity score reweighting.

[16] To be parallel with the subsequent propensity score analysis, column (4) of row 2 shows our baseline estimate that re-weights on county and risk score bin, while column (3) shows the impact of re-weighting only on risk score

Row 3 shows that (not surprisingly) using county and risk score as in our baseline approach, but through a propensity score, has essentially no effect on the results. Rows 4 through 6 then use the individual components of the risk score separately as observables x_i in the propensity score; specifically we now include increasingly flexible controls for age, gender, dual eligibility, and 70 hierarchical condition categories (HCC) indicator variables. These alternative specifications have very little effect on the results; indeed, more flexible controls result in slightly higher estimated TM spending and thus greater MA-TM spending differences.

7.3 Using mortality to correct for selection on unobservables

We try to address selection on unobservables that are correlated with healthcare spending by leveraging the fact that, fortunately, we can observe mortality outcomes for individuals in both TM and MA. As we saw in Table 1, mortality is lower for MA enrollees than for TM enrollees; it is also lower conditional on county and risk score (not shown).

We therefore use mortality differences across enrollees in MA and TM to try to proxy for unobservable differences in expected healthcare spending. We make the strong assumption that mortality outcomes are unaffected by enrollment in MA. Under this assumption, we can use mortality as an additional observable and control for it.

This use of mortality to proxy for unobservables is of course not perfect; but we think it provides a reasonably aggressive bounding approach to the likely role of unobservables. The results using mortality will under-estimate the impact of MA on reducing healthcare spending relative to TM if in fact some of the mortality differences between MA and TM reflect a beneficial treatment effect of MA on mortality, or if, conditional on mortality, counterfactual TM spending would be higher for individuals who select into MA than for those who do not. Likewise, it will over-estimate the impact of MA on reducing healthcare spending if MA increases mortality or if, conditional on mortality, counterfactual TM spending would be lower for individuals who select into MA than for those who do not. It is not obvious what the sign of any bias would be.

We pursue two approaches: a statistical correction in the spirit of our approach to adjusting for observables, and an "economic" selection model.

Statistical correction We use differences in mortality rates to create an MA-specific mapping and a TM-specific mapping from risk scores to a health index, captured by mortality. This approach therefore captures differences in expected spending, conditional on risk score, arising from unobservable health differences captured by mortality. Such differences in expected spending could reflect selection on unobserved health, as well as upcoding (manipulation of patient diagnoses and hence risk scores) in MA beyond what CMS assumes (Geruso and Layton 2015).

Specifically, we calculate a predicted mortality rate by risk score bin, separately for MA and TM enrollees. We can then reweight on predicted mortality (row 7 of Table 9) or on a propensity score that uses predicted mortality as the observable (row 8 of Table 9); here we once again estimate the

bin.

propensity score county by county. These specifications, which effectively match MA enrollees to TM enrollees with the same mortality rate (and therefore lower risk scores of the MA enrollees) lead to the largest estimate of selection. According to these estimates, total spending in MA is only 8-10 percent lower than in TM.[17]

Parametric Selection Model We also consider a more parametric selection model as an alternative way to adjust for observables and unobservables. It yields a less aggressive correction for unobservables than the statistical correction shown in the last two rows of Table 9.

In this alternative approach, we continue to assume that mortality is not affected by enrollment in MA. We also assume that there is only one dimension of unobservable heterogeneity – which we can think of as health status – which affects both costs (under TM) and mortality. Under these assumptions, we can essentially use mortality rate as a "control function" for unobservables.

Specifically, we assume the data generating process arise from two equations. The first is a selection equation

$$W_i = \mathbf{1}\{u(x_i, r_i, \eta_i) \leq 0\}, \tag{7}$$

where x_i is a vector of observables associated with beneficiary i, r_i is her risk score, and η_i is unobserved. The second equation is the potential outcome equation

$$E(\ln c_i^{TM}|x_i, r_i, \theta_i) = x_i'\alpha_x + \alpha_r(r_i + \theta_i). \tag{8}$$

We depart from the analysis thus far and consider the outcome to be log costs rather than dollars since it seems more natural to model factors (either observable or unobservable) as affecting cost proportionally.

Under these assumptions, the selection term (see equation (6)) is given by

$$S \equiv E\left[\ln c_i^{TM}|W_i = 1\right] - E\left[\ln c_i^{TM}|W_i = 0\right] = \alpha_r(E(\theta_i|x_i, r_i, W_i = 1) - E(\theta_i|x_i, r_i, W_i = 0)), \tag{9}$$

and the selection term is not zero when η_i and θ_i are correlated.

Suppose now that mortality realization is drawn from a logistic distribution, so that

$$E[m_i|x_i, r_i, \theta_i] = \frac{\exp\left(x_i'\beta_x + \beta_r\left(r_i + \theta_i\right)\right)}{1 + \exp\left(x_i'\beta_x + \beta_r\left(r_i + \theta_i\right)\right)},$$

where $m_i = 1$ if the beneficiary (in either TM or MA) dies during the year (2010) and $m_i = 0$ otherwise. We can now define the log-odds ratio

$$\widetilde{m}_i(x_i, r_i, \theta_i) = \ln \frac{E[m_i|x_i, r_i, \theta_i]}{1 - E[m_i|x_i, r_i, \theta_i]} = x_i'\beta_x + \beta_r\left(r_i + \theta_i\right). \tag{10}$$

[17] By way of comparison, Geruso and Layton (2015) estimate that MA risk scores are 6 to 16 percent higher than they would be for the same enrollee under TM, or 3 to 13 percent higher after accounting for CMS' "upcoding" adjustment to MA risk scores (that we have already applied). Taking their upper bound, such 13% additional "upcoding" alone would suggest that comparable TM spending would be $744 per enrollee-month (13% lower than our baseline estimate of $855), which would imply that MA costs ($642) are 14 percent lower than in TM. Put differently, the upper bound of their upcoding estimate could account for most of the selection on unboservables we estimate here.

Equation (10) is estimable for the entire population, using the CMS data set, as we see mortality there for both the TM and MA populations. We can thus obtain unbiased estimates for β_x and β_r and back out $E(\theta_i|x_i, r_i, W_i)$. Equipped with this information, we can return to equation (8) and correct for the selection. That is, we can now regress $y_i'(x_i, r_i) = E(y_i^{TM}|x_i, r_i)$ on x_i and on $r_i + E(\theta_i|x_i, r_i, W_i = 0)$ and (given our assumptions) obtain unbiased estimates for α_x and α_r. We then have all the pieces to plug into the selection term, equation (9), and obtain the extent of selection on unobservables.

This approach yields that 16% of the residual difference in total spending between MA and (reweighted) TM is attributable to selection on unobservables. That is, we use equation (4), substituting $\ln c_i^{TM}$ for y_i^{TM} (using the reweighted cost) to compute the total difference in log cost and obtain 0.497. We then follow the above procedure to estimate S (see equation (9)), and we obtain 0.0786, which is 16% of the overall difference.

8 Conclusion

We have compared healthcare spending and utilization in public and private Medicare. This setting provides a rare opportunity for a "side by side" comparison of public and private health insurance systems operating on a similar scale, for the same population, in the same markets, and with the same providers. Novel data from the Health Care Cost Institute on the healthcare claims of MA enrollees allow us a rare look inside the "black box" of healthcare utilization and spending in MA.

We find that MA insurer revenues are 30 percent higher than their healthcare spending. Healthcare spending for enrollees in MA is 25% lower than for enrollees in TM in the same county and risk score. We explore a variety of ways to quantify how much of this overall difference may be driven by residual selection; in our most aggressive adjustment, we find that the spending difference between MA and TM shrinks to 8%.

The lower spending by MA enrollees is entirely due to lower healthcare utilization. Prices appear similar in MA and TM. Where we can most directly measure this – the price of an admission for a given DRG at a given hospital – we estimate that average prices in MA are 1.1% higher than in TM. Reductions in utilization appear similar both for types of care where there is concern about "over use" (e.g. imaging and diagnostic tests) and where there is concern about "under use" (e.g. preventive care).

We provide suggestive evidence for some of the potential channels by which MA may reduce healthcare utilization for enrollees. We find that utilization is lower in MA but that, conditional on an encounter, spending per encounter is similar or slightly higher in MA. This suggests that MA manages to restrict utilization on the margin to sicker individuals. Relatedly, individuals discharged from the hospital are much more likely to be sent home – and less likely to be sent to post-acute care facility – if they are enrolled in MA rather than in TM. We also find evidence consistent with substitution to less expensive types of care in MA: differences in specialist visits are much larger than differences in primary care visits, and while inpatient surgery rates are lower in MA, outpatient surgery rates are higher.

Finally, in light of the widespread interest in geographic variation in healthcare spending in TM, and recent work on geographic variation in commercial (under 65) private insurance, we explore similar comparisons in MA. Although geographic variation in spending in TM is often viewed as a reflection of the inefficiencies in a public health insurance system, we find similar – in fact slightly larger – geographic variation in spending in MA compared to TM. And while recent work has emphasized the much greater geographic pricing variation in private commercial insurance than in TM, we find similar – in fact slightly smaller – geographic variation in pricing in MA compared to TM.

One natural question these findings raise is their implications for MA insurers and consumers. For insurers, our estimates from MA data indicate that their revenue exceeds their healthcare expenditures by \$177 (about 30%) per enrollee-month. An important area for further work is to examine how this may be dissipated through other costs, such as the administrative costs of providing the insurance and the marketing costs of attracting enrollees. A related and important question is whether and how competitive pressures affect the MA market.

Implications for consumers are more elusive, since the elements of their objective function are not as straightforward to define or measure. A simple revealed preference argument would suggest that consumers who choose MA are better off in it. Other inferences are harder to make. Quality of the healthcare experience is difficult to assess; our measures of preventive care point to reductions there that are similar in magnitude to those for other forms of care. We calculated that the mean actuarial benefit to consumers (i.e. rebate to consumers as measured in the bid data) was \$51 per enrollee-month, but, of course, the rebate may be valued differently from its actuarial value, and MA plans have other attributes that will affect consumer surplus, such as limited networks. The implications of privately provided Medicare for both consumers and producers is an important area for further work.

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Figure 1: MA penetration over time

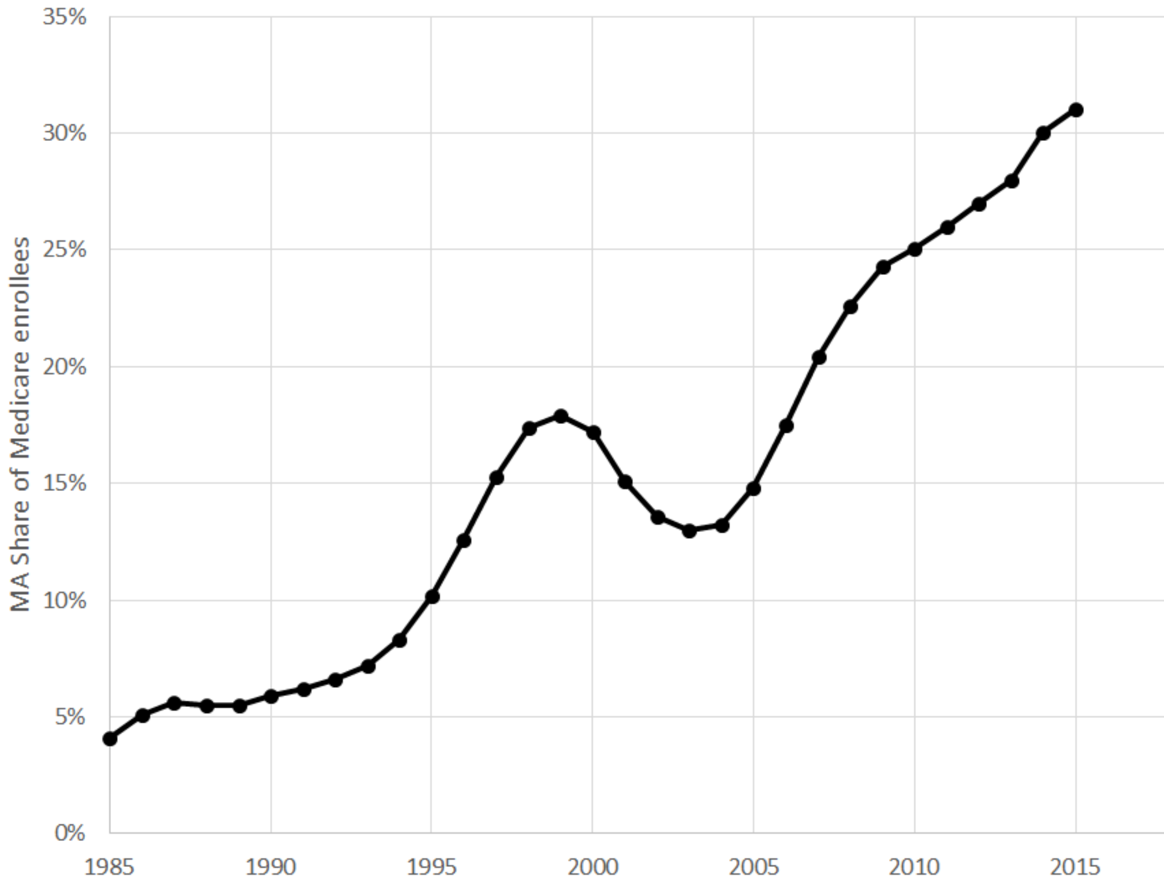

Figure shows the share of Medicare beneficiaries enrolled in Medicare Advantage plans, year by year. The data source is CMS's Medicare Managed Care Contract Plans Monthly Summary Reports. All data are from December of the year indicated.

Figure 2: State-by-State Comparison of TM and MA Spending

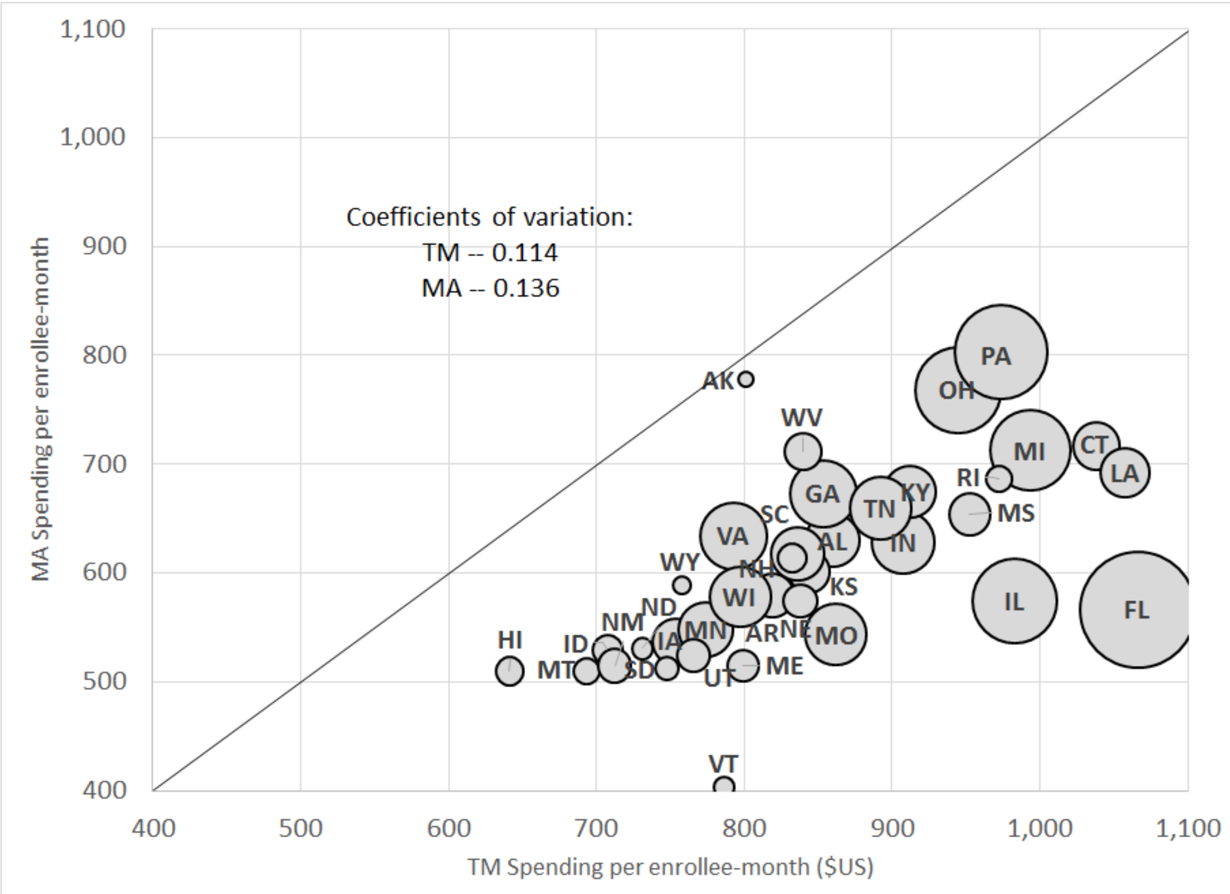

Figure plots MA spending per enrollee-month against TM spending per enrollee-month for each of the 36 states in our baseline sample. Coefficients of variation across states in spending are computed using total Medicare enrollees in the state as weight. The size of each bubble is proportional to the number of total Medicare enrollees in the state.

Figure 3: TM-MA Spending Differences across States

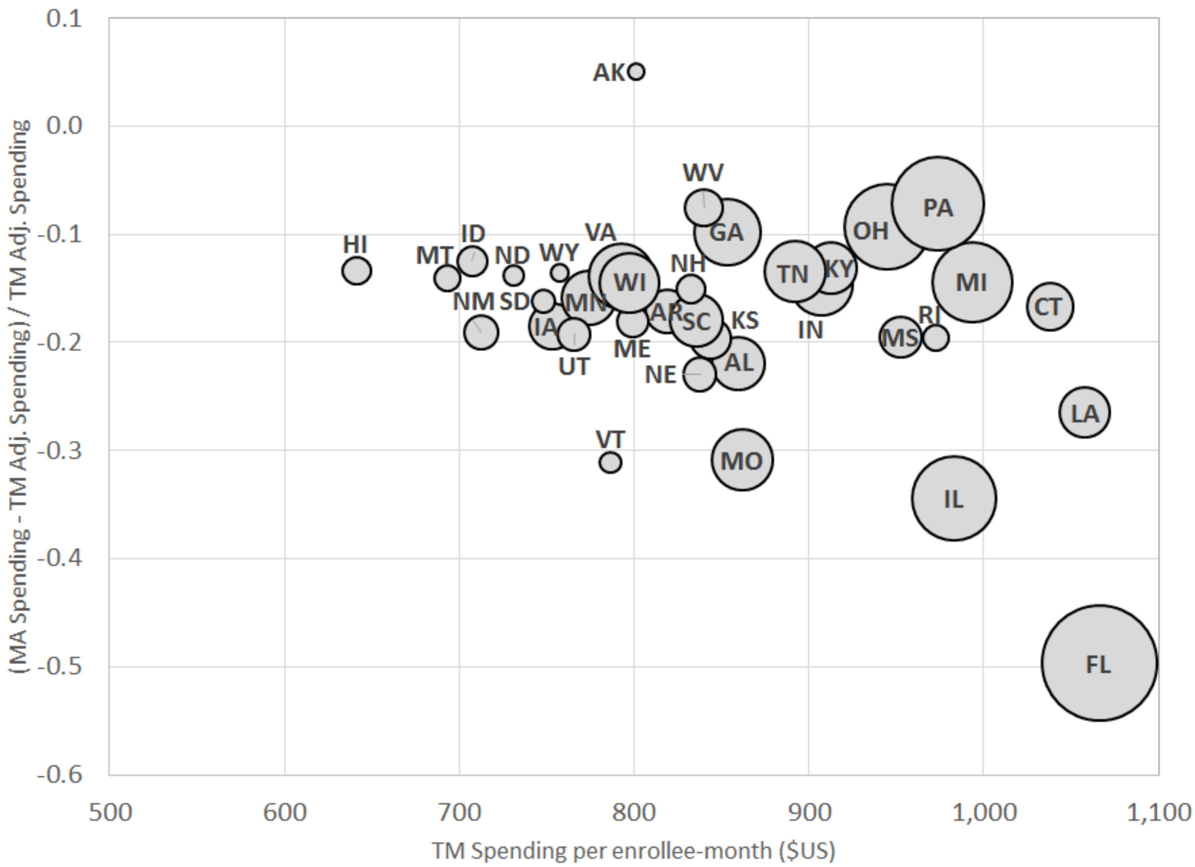

Figure plots the (percentage) difference between average MA spending and (re-weighted) TM spending per enrollee-month against average TM spending for each of the 36 states in our baseline sample. The size of each bubble is proportional to the number of total Medicare enrollees in the state. The y-axis compares MA spending to TM spending that is re-weighted to match the MA population on county and risk score, using our preferred weighting (see Table 2, column (4)). The x-axis reports average (unadjusted) TM spending in the state (see Table 2, column (1)).

Figure 4: TM-MA price differences for inpatient admissions, across DRGs

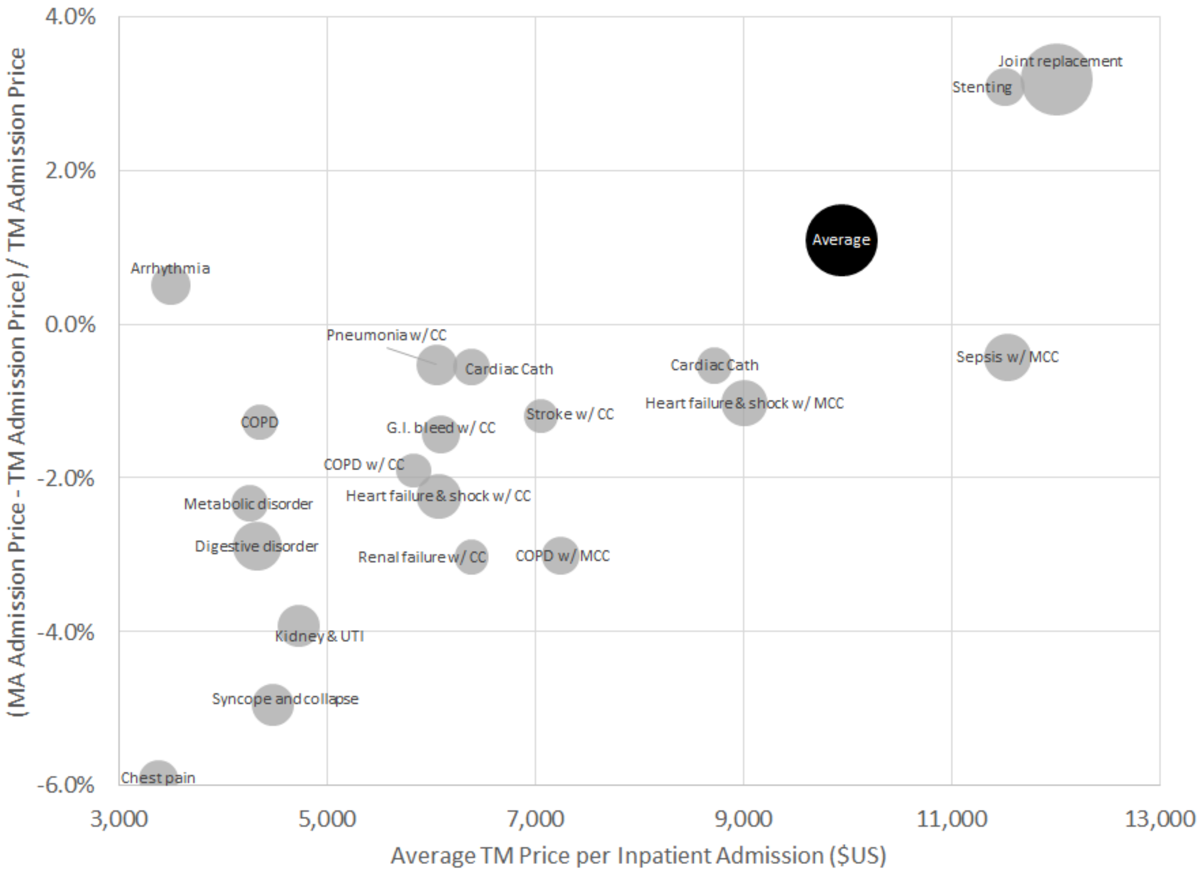

Figure plots the (percentage) difference between average MA prices and TM prices for a hospital admission, overall and for the 20 most common DRGs in MA. Average MA or TM prices for a given DRG are computed using a common (MA) basket of state admission shares for that DRG. The national average price in MA or TM is computed by weighting each DRG (including the less common ones not shown here) by its (national) share of MA admissions. The size of each bubble (except for the overall "Average" bubble) is proportional to the number of MA admissions with that DRG.

Figure 5: TM-MA price differences for inpatient admissions, across states

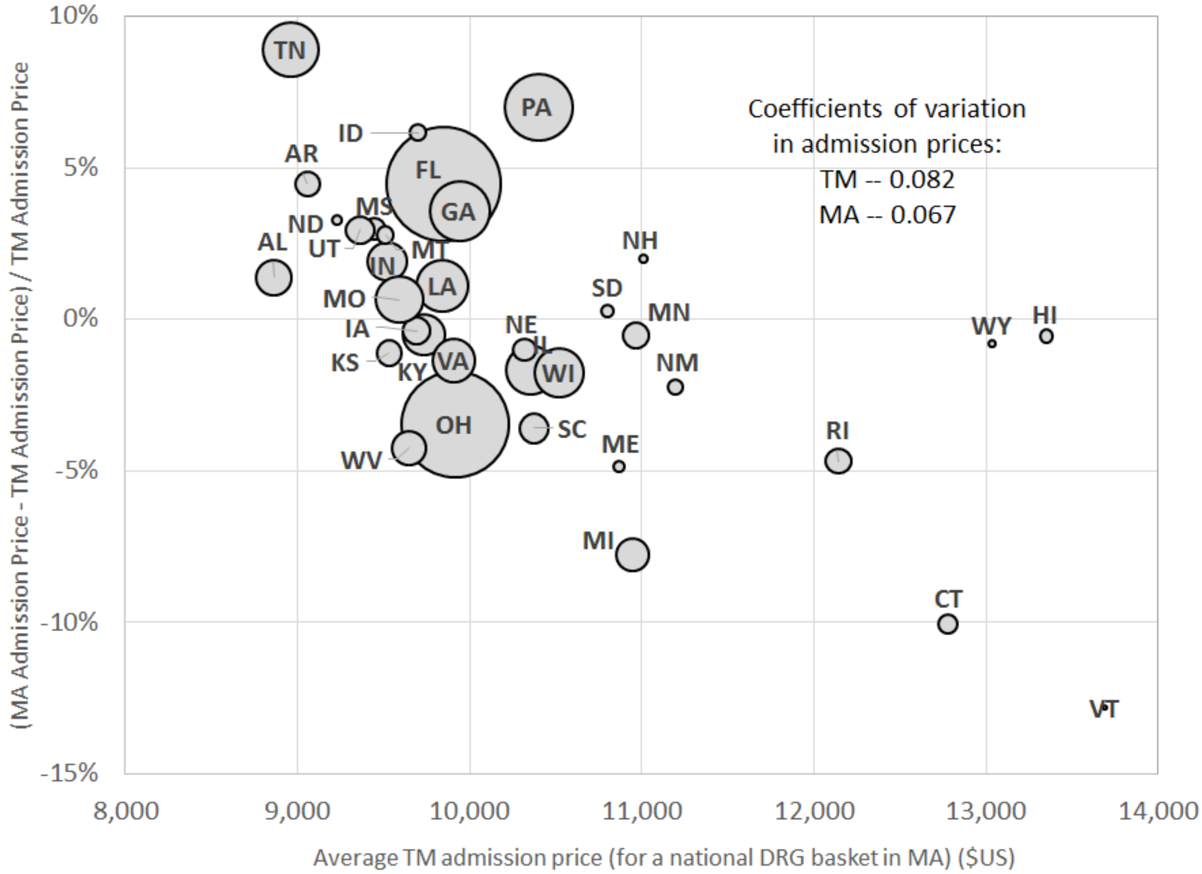

Figure plots the (percentage) difference between average MA prices and TM prices for a hospital admission for each state in our baseline sample (except Alaska which is omitted because it has too few inpatient admissions for us to report). Averages are computed for each state using a common (MA) "basket" of DRG admission shares. The size of each bubble is proportional to the number of MA admissions in that state. Coefficients of variation across states in prices are computed using total Medicare enrollees in the state as weight.

Table 1: Baseline sample

Data source / sample	All CMS[a]			Baseline CMS[b]			All HCCI[a]	Baseline HCCI[b]
	TM	MA (all insurers)	MA (HCCI insurers)	TM	MA (all insurers)	MA (HCCI insurers)	MA (HCCI insurers)	MA (HCCI insurers)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Enrollee-level summary[c]								
No. of enrollees (000s)	26,420	10,475	3,911	15,641	5,291	2,270	2,941	2,290
Female	0.575	0.574	0.574	0.576	0.567	0.568	0.569	0.571
Age	75.4	74.6	74.5	75.4	74.3	74.1	--	--
Coarse age:[d]								
65-74	0.520	0.555	0.560	0.516	0.568	0.581	0.592	0.590
75-84	0.330	0.328	0.325	0.333	0.323	0.315	0.306	0.308
85+	0.150	0.117	0.115	0.151	0.109	0.104	0.102	0.102
Dual eligible	0.143	0.123	0.111	0.129	0.072	0.073	--	--
SNP enrollees	--	0.081	0.065	--	0.000	0.000	0.0	0.0
Risk score	1.089	1.031	1.032	1.085	0.986	0.994	--	--
Died in 2010	0.050	0.039	0.039	0.052	0.036	0.036	--	--
Panel B: Spending per enrollee-month[e]								
No. of enrollee-months (000s)	304,908	118,737	44,371	180,608	60,273	25,867	32,506	25,394
Total Spending ($/month)	938	--	--	911	--	--	639	642
Insurer Spending ($/month)	798	--	--	771	--	--	586	590
OOP Spending ($/month)[f]	140	--	--	140	--	--	53	52
Panel C: Payments to insurers per enrollee-month[e]								
Overall CMS expenditure ($)[g]	--	820	819	--	767	778	--	--
Actuarial value of incremental consumer benefits ($)[h]	--	63	53	--	56	51	--	--
Plan payments for organic MA services ($)[i]	--	800	806	--	751	767	--	--

Table presents summary statistics for various sample definitions. Columns (6) and (8), highlighted in gray, are comparable and are used to validate our sample construction.

[a] Sample include all Medicare enrollees who are 65 or older by the end of 2010.

[b] Baseline sample excludes SNP enrollees, and enrollees in the 15 states in which the number of enrollee-months in HCCI is not within 10% of that in CMS.

[c] At the enrollee-level, we define an individual as enrolled in TM if she is never enrolled in MA during the sample year and is enrolled in TM for at least one month of the sample year; we define her as enrolled in MA if she is enrolled in MA in any month of the year, and we assign her to an HCCI insurer if she is covered by one of them in her first month in MA. Age, dual eligibility and SNP enrollment is likewise defined based on the first month in which an enrollee is observed during the sample year.

[d] In HCCI we only have information about age in three bins: 65-74, 75-84, and 85+.

[e] We count an enrollee-month in TM if she is enrolled in TM that month and never enrolled in MA during the sample year; any enrollee-months in MA (or in HCCI insurers) are counted as such.

[f] Out of pocket (OOP) spending denotes amount owed by enrollee. For TM enrollees, OOP Spending may be partially covered by supplemental (Medigap or employer-sponsored) coverage.

[g] This includes all payments made from CMS to the MA plans, including risk-adjusted payments and rebates.

[h] This is also known as the "rebate."

[i] The variable "Plan payments for organic MA services ($)" is equal to "Overall CMS expenditure ($)" plus additional premiums paid by the beneficiaries minus the non-cost-sharing component of the rebate.

Table 2: Baseline reweighting

Source	CMS				HCCI
Sample	TM	TM	TM	TM	MA
Reweight by	None	County	County & Risk bin 0.5	County & Risk bin 0.1	None
	(1)	(2)	(3)	(4)	(5)
No. of enrollee-months (000s)	180,608	180,608	180,608	180,608	25,394
Total Spending ($/month)	911	942	857	855	642
Insurer Spending ($/month)	771	799	725	723	590
OOP Spending ($/month)[a]	140	143	132	131	52

Results based on baseline sample (see Table 1, columns 8 and 4). All statistics are at the enrollee-month level.

[a] Out of pocket (OOP) spending denotes amount owed by enrollee. For TM enrollees, OOP Spending may be partially covered by supplemental (Medigap or employer-sponsored) coverage.

Table 3: Spending differences for different groups of enrollees

	% MA enrollees	TM, unweighted	TM, weighted[a]	MA	Difference	
					(4)-(3)	((4)-(3)) / (3)
	(1)	(2)	(3)	(4)	(5)	(6)
No. of enrollee-months (000s)	25,394	180,608	180,608	25,394		
Total Spending	100%	911	855	642	-212	-24.9%
Panel A. Spending ($/month) by enrollee characteristics						
Male	42.9%	916	857	673	-184	-21.4%
Female	57.1%	907	853	619	-234	-27.4%
65-74	56.3%	723	661	540	-120	-18.2%
75-84	32.6%	1,022	967	731	-236	-24.4%
85+	11.1%	1,264	1,276	898	-378	-29.6%
Urban[b]	76.8%	942	887	645	-243	-27.3%
Rural[b]	23.2%	851	752	634	-118	-15.7%
Panel B. Realized distribution of spending ($/month)						
Proportion w/ no spending		0.37	0.38	0.46	0.08	19.6%
Median spending		93	84	38	-46	-54.3%
75th pctile		332	317	222	-95	-30.0%
90th pctile		1,314	1,233	849	-384	-31.1%
95th pctile		3,433	3,124	2,161	-964	-30.8%
97.5th pctile		8,349	7,571	5,690	-1,880	-24.8%
99th pctile		18,510	17,332	13,614	-3,718	-21.5%

Results based on baseline sample (See Table 1, columns 8 and 4). All statistics are at the enrollee-month level. All spending numbers are in $/month.

[a] Weighting based on our preferred weighting, as in column (4) in Table 2.

[b] Rural/urban assignment is based on whether the enrollee zip code is in an MSA.

Table 4: Spending differences for different components of spending

	TM, unweighted	TM, weighted[a]	MA	Difference	
				(3)-(2)	((3)-(2)) / (2)
	(1)	(2)	(3)	(4)	(5)
No. of enrollee-months (000s)	180,608	180,608	25,394		
Total spending[b]	911	855	642	-212	-24.9%
Inpatient	364	333	269	-64	-19.2%
Outpatient	452	435	328	-107	-24.6%
Skilled Nursing Facilty (SNF)	95	86	45	-42	-48.2%
Hospice[c]	31	32	24	-8	-24.9%

Results based on baseline sample (See Table 1, columns 8 and 4). All statistics are at the enrollee-month level. All spending numbers are in $/month.

[a] Weighting based on our preferred weighting, as in column (4) in Table 2.

[b] Total spending is the sum of inpatient, outpatient, and skilled nursing facility (SNF) spending. It doesn't include hospice.

[c] Hospice expenditures for MA enrollees are billed directly to CMS, so for MA enrollees they are in fact observed in the CMS data and not in the HCCI data.

Table 5: Differences in healthcare utilization

	TM, unweighted	TM, weighted[a]	MA	Difference	
				(3)-(2)	((3)-(2)) / (2)
	(1)	(2)	(3)	(4)	(5)
Total spending ($/month)	911	855	642	-212	-24.9%
Inpatient days	0.200	0.181	0.144	-0.037	-20.6%
Any inpatient admission	0.027	0.025	0.021	-0.004	-16.0%
Days cond'l on any	7.371	7.352	6.95	-0.402	-5.5%
Skilled Nursing Facility (SNF) days	0.336	0.296	0.131	-0.166	-55.9%
Days cond'l on any	47.275	46.654	20.6	-26.0	-55.8%
Emergency Department (ED) Visits	0.049	0.045	0.038	-0.007	-15.8%
Outpatient ED visits	0.031	0.028	0.024	-0.004	-14.8%
Inpatient ED visits	0.018	0.017	0.014	-0.003	-17.5%
Physician visits	1.22	1.21	1.01	-0.204	-16.8%
Any physician visits	0.545	0.540	0.486	-0.054	-10.0%
Number of visits cond'l on any	2.24	2.25	2.08	-0.169	-7.5%

Results based on baseline sample (See Table 1, columns 8 and 4). All statistics are at the enrollee-month level, but all days associated with a given encounter are attributed to the original admission date, even if it extends beyond the month.

[a] Weighting based on our preferred weighting, as in column (4) in Table 2.

Table 6: Utilization differences across different types of care

	TM, unweighted[a]	TM, weighted[a]	MA	Difference	
				(3)-(2)	((3)-(2)) / (2)
	(1)	(2)	(3)	(4)	
A. Testing and imaging					
Diagnostic tests	2.12	2.05	1.55	-0.50	-24.4%
Any diagnostic test	0.35	0.34	0.293	-0.049	-14.3%
Cond'l on any	5.97	6.00	5.29	-0.71	-11.9%
Imaging procedures	0.66	0.64	0.52	-0.12	-18.9%
Any imaging test	0.18	0.17	0.154	-0.018	-10.5%
Cond'l on any	3.75	3.71	3.37	-0.35	-9.3%
B. Preventative care (rates per relevant population)[b]					
Flu shot	0.051	0.050	0.032	-0.018	-38.0%
Cardiovascular screen	0.090	0.093	0.077	-0.016	-16.9%
Colorectal cancer screen	0.009	0.010	0.008	-0.001	-14.9%
Mammogram	0.045	0.046	0.047	0.001	3.3%
Pap smear	0.011	0.012	0.013	0.001	7.9%
Prostate cancer screen	0.023	0.023	0.018	-0.005	-22.4%
Hemoglobin A1c test	0.064	0.062	0.055	-0.007	-14.1%
Blood lipids test	0.103	0.106	0.091	-0.016	-15.9%
Eye exam	0.067	0.067	0.054	-0.014	-21.1%
C. Appropriateness of ED Visits					
Nonemergent	0.006	0.005	0.005	-0.001	-14.7%
Emergent					
ED care not needed (primary care treatable)	0.012	0.011	0.009	-0.002	-15.8%
ED care needed, preventable	0.004	0.004	0.003	-0.001	-18.4%
ED care needed, not preventable	0.012	0.011	0.009	-0.002	-16.6%
Unclassified	0.013	0.012	0.010	-0.002	-19.9%

Results based on baseline sample (See Table 1, columns 8 and 4). All statistics are at the enrollee-month level.

[a] Weighting based on our preferred weighting, as in column (4) in Table 2.

[b] Rates are per the relevant population, which is: everyone for flu shot, cardiovascular screen, and colorectal cancer screen; women for pap smear; women aged 65-74 for mammogram; men for prostate cancer screen; and enrollees aged 65-74 with a diabetes diagnosis for hemoglobin test, blood lipids test, and eye exam.

Table 7: Differences in spending per episode of care

	TM, unweighted	TM, weighted[a]	MA	Difference	
				(3)-(2)	((3)-(2)) / (2)
	(1)	(2)	(3)	(4)	(5)
Total spending ($/month)	911	855	642	-212	-24.9%
Spending per SNF day	381	379	378	-1	-0.2%
Spending per outpatient ED visit	782	768	837	69	9.0%
Inpatient[b]:					
Spending per admission	10,134	10,151	10,093	-58	-0.6%
Spending per day	1,901	1,903	1,908	6	0.3%
Spending per AMI admission	14,512	14,558	14,761	203	1.4%
Spending per AMI day	2,730	2,739	2,663	-77	-2.8%

Results based on baseline sample (See Table 1, columns 8 and 4). All statistics are at the enrollee-month level, but all expenditures or days associated with a given encounter are attributed to the original admission date, even if it extends beyond the month.

[a] Weighting based on our preferred weighting, as in column (4) in Table 2.

[b] Inpatient spending here includes only payments to the hospital, it does not include associated physician payments as in prior tables.

Table 8: Potential channels for cost saving

	TM, unweighted[a]	TM, weighted[a]	MA	Difference	
				(3)-(2)	((3)-(2)) / (2)
	(1)	(2)	(3)	(4)	(5)
A. Hospital discharge destinations:					
Home	0.0136	0.0122	0.0109	-0.0013	-10.4%
Home health service org.	0.0053	0.0049	0.0038	-0.0011	-23.3%
SNF	0.0067	0.0061	0.0038	-0.0023	-37.6%
Other post-acute care	0.0014	0.0013	0.0004	-0.0009	-70.5%
Other (incl. hospice, death)	0.0027	0.0024	0.0018	-0.0007	-27.3%
B. Surgeries and specialists:					
Total surgeries	0.037	0.033	0.039	0.006	18.1%
Outpatient surgeries	0.029	0.026	0.032	0.007	25.5%
Inpatient surgeries	0.008	0.007	0.007	-0.001	-7.2%
Primary care visits	0.379	0.370	0.355	-0.014	-3.8%
Specialist visits	0.840	0.844	0.655	-0.190	-22.4%

Results based on baseline sample (See Table 1, columns 8 and 4). All statistics are at the enrollee-month level. All spending numbers are in \$/month. Panel A reports (unconditional) hospital discharge destinations.

[a] Weighting based on our preferred weighting, as in column (4) in Table 2.

Table 9: Alternative ways to correct for selection into MA

Reweight on	Covariates	TM Mean Total Spending (Reweighted)	
		Reweight nationally	Reweight county-by-county
(1)	(2)	(3)	(4)
1. None		911	911
2. Risk score[a]	--	844	855
3. Prop. Score[e]	county*risk score	853	854
4. Prop. Score[e]	county*(age FE, female, HCC FE)[b]	883	884
5. Prop. Score[e]	county*(age FE, female, HCC FE, dual)[c]	864	866
6. Prop. Score[e]	county*dual*(age FE, female, HCC FE)[d]	864	861
7. Predicted mortality[f]		698	706
8. Prop. score	county*predicted mortality[e]	712	709

Results based on baseline sample (See Table 1, column 4). Rows 2 and 7 use our baseline re-weighting approach (see equation (2)) with the re-weighting based on risk score bin (row 2) or predicted mortality bin (row 7). The "propensity score" approach in rows 3-6 and row 8 is based on a logistic regression (estimated separately, county by county) for being in MA, using the covariates listed in Column (2).

[a] Risk scores are mapped to 0.1 bins, and are included using indicator variables for each bin.

[b] The independent variables are dummies for age, gender, and the 70 hierarchical condition categories (HCCs) that appear in the MA risk adjustment model.

[c] The independent variables are dummies for age, gender, the 70 hierarchical condition categories (HCCs) that appear in the MA risk adjustment model, and dual eligibility for Medicare and Medicaid.

[d] The independent variables are dummies for age, gender, and the 70 hierarchical condition categories (HCCs) that appear in the MA risk adjustment model. Each of these dummies is interacted with a dummy for dual eligibility for Medicare and Medicaid.

[e] Resultant propensity score is mapped to bins of 0.01, and included as indicator variables for each bin.

[f] "Predicted mortality" is generated based on a regression of a annual mortality indicator on indicators for risk bins of 0.1. The regression is run separately for MA enrollees and for TM enrollees. The resultant mortality prediction is mapped to bins of 0.001, and included as indicator variables for each bin.

Appendix A: Construction of the baseline sample

A.1 Raw data files

HCCI Files We have data from HCCI on a convenience sample of 2010 Medicare Advantage (MA) enrollees in three insurers: Aetna, Humana, and UnitedHealthcare (hereafter, "HCCI insurers"). The data were provided to HCCI by the private insurers and exclude enrollees in highly capitated plans, Special Needs Plans, plans with various data issues, and other limitations.[18]

The HCCI data contain four main files. There is an enrollment file, which we use to define the sample and obtain basic demographic information. The unit of observation is an enrollee-month. The enrollment file contains monthly indicators for enrollment, age (in bins of 10 years), gender, the enrollee's state of residence, and the enrollee zip code (masked for zip codes with a 2010 census population of less than 1,350).[19] We observe "exit" within the year from the HCCI data but do not directly measure mortality. The data also contain an indicator as to whether the plan covering the enrollee is HMO, PPO, or other, but do not contain information as to the identity of the insurer or other coverage details. In addition, there are three claims files – inpatient, outpatient, and physician – which we use to measure medical spending. In these files the unit of observation is a claim, payable by one of the HCCI insurers to a medical provider.

CMS Files We have data from CMS on the universe of individuals enrolled in Medicare at any point in 2010. This includes both those enrolled in Traditional Medicare (TM) and those enrolled in MA. For all enrollees – both those in TM and those in MA – we have four main files: the enrollment data base (EDB), the common Medicare enrollment file (CME), the Health Plan Management System (HPMS), and the Risk Adjustment Processing System (RAPS). The two enrollment files allow us to observe for every enrollee: exact date of birth, date of death (if applicable), gender, and zip code. They also include monthly data on whether the individual is enrolled in TM Part A, enrolled in TM Part B, enrolled in MA, whether they are dually covered by Medicare and Medicaid, and whether the individual died; note that dual coverage and mortality are observed in the CMS files for both MA and TM enrollees.

For enrollee-months in MA we also observe a plan identifier. Using the HPMS plan-level data on the parent organization, we are able to identify which plans are provided by the HCCI insurers, and also whether the plan is a Special Needs Plan (SNP), specialized Medicare Advantage plans for particular types of individuals (e.g. those in long term care institutions). We assign an MA enrollee an MA plan based on the first plan in which she is enrolled in the year.

The RAPS file has a risk score and indicators for each health indicator (HCC) that goes into the calculation of the risk score, for every enrollee. These HCCs are then integrated using a predictive

[18] The description of the exclusion critiera come from HCCI, except for the exclusion of SNPs which we determined by looking at the type of plan codes that apopear in the HCCI enrollment file.

[19] When we analyze counties separately by urban/rural status, we assume the pseudo counties are rural, since 2010 census data indicate that 80 percent of them are in fact rural.

formula that combines them together to form a risk score, which is a predictor of the enrollee's healthcare spending in the subsequent year. We observe these indicator for MA enrollees since MA plans must submit HCCs to CMS to determine their CMS payments. The RAPS file also contains indicators for the enrollees' type – community (90%), new (9%), or long-term institutional (1%) – and three risk scores (one for each type), and we assign each enrollee her type-specific risk score.

For TM enrollees only, the CMS data allows us to measure healthcare utilization and spending through 6 claims files: inpatient, outpatient, SNF, home health, durable medical equipment, and physician. A seventh claims file – the hospice claims file – contains utilization and spending for both TM and MA enrollees (since hospice is reimbursed by CMS for MA enrollees as well as TM enrollees); the hospice file is the only CMS file where we can observe utilization and spending for MA enrollees.

Finally, for MA enrollees we use the Monthly Membership Detail Report and the HPMS to construct information on revenues to MA insurers. Specifically, for each individual enrolled in an MA plan, we observe the payment from CMS to the insurer. The payment from CMS to the insurer consists of a part that is retained by the insurer and the rebate which is passed on by the insurer to the enrollee. We observe, for each plan, this rebate amount, as well as the Part C premium that is paid by the enrollee to the insurer. We define MA revenue for a given enrollee-month as the payments from CMS to the insurer minus the rebate to consumers, plus the Part C premiums.

A.2 Sample definition

We use the HCCI data to analyze spending and healthcare utilization for individuals covered by the HCCI insurers. We use the CMS data for two primary purposes: to construct comparison spending and healthcare utilization estimates for "comparable" TM enrollees, and to create an independent measure of enrollment in the HCCI insurers' plans that we use to examine and validate the completeness of the HCCI enrollment data. Both of these exercises require that we define a TM and an MA enrollee in the CMS data.

Throughout this paper, in the CMS data we define an enrollee as enrolled in MA if she is enrolled in MA for at least one month during 2010; we define someone as enrolled in TM if she is not enrolled in MA during any month in 2010, and is enrolled in TM Part A and TM Part B in at least one month during 2010. We count the enrollee-months in MA as the total number of months in MA during the year. Within MA, we can further identify the subset of MA enrollees who are in the three HCCI insurers. We restrict our analysis to enrollee-months who are 65 and over, who reside in one of the 50 states or the District of Columbia; we do not require individuals to be enrolled for a full year.

We can measure the completeness of the HCCI data in terms of enrollment by the HCCI insurers by comparing enrollee-month counts in the HCCI data to enrollee-month counts for these HCCI insurers in the CMS data, which in principle records the universe of enrollees in those same plans. Appendix Table A1 shows enrollee-month counts for the three HCCI insurers according to the HCCI data and the CMS data, overall, and separately by state. To analyze how "complete" the HCCI data are, we compare counts of enrollee-month by state in the HCCI data (column 3) to analogous counts of enrollee-months in the HCCI insurers by state in the CMS data (column 5); we exclude from the CMS comparison enrollment counts in the HCCI insurers any enrollees in SNP plans since, as discussed, these are also excluded from the HCCI data. The HCCI data contain about 78 percent of total MA enrollees for the HCCI insurers; "missing" enrollees disproportionately concentrated in the Western US.

We restrict our analysis to the 36 "complete data" states, which we define as states where the count of enrollee-months in HCCI is within 10 percent of the corresponding count in CMS data. The 10 percent cutoff is arbitrary, but 30 of the 36 states are within 5 percent, and these 30 states would account for more than 70% of the enrollees in the baseline sample, so the results are unlikely to change much with more conservative sample definitions. Overall, a comparison of column 8 and column 6 of Table 1 shows that our baseline sample in HCCI has 1 percent more enrollees than the pseudo HCCI enrollment data set we create for the same baseline sample in CMS; this is in line with what we would expect, given that plan enrollment data is missing in CMS for 1 percent of MA enrollees.

Columns (1) and (2) of Appendix Table A1 show, by state, the MA share of Medicare enrollment and the HCCI insurer share of MA. Overall, the 36 states that we analyze comprise 61 percent of enrollment in HCCI insurers nation-wide. As can be seen in Appendix Figure A1, the states that are omitted from our baseline analysis are disproportionately in the Western US.

Appendix B: Construction of specific variables

We analyze MA medical spending and utilization in the HCCI data. We benchmark it against TM spending and utilization in the CMS data, for observably similar enrollees. We therefore construct parallel medical spending and healthcare utilization variables in the HCCI and CMS data. Unless explicitly noted, all MA medical spending and healthcare utilization measures are derived from HCCI data, and all TM spending measures are derived from CMS data. All measures are constructed at the enrollee-month level unless explicitly noted.

Total spending is defined as the sum of insurer spending plus out-of-pocket spending. **Insurer spending** is defined based on the actual amount paid by the plan (either MA or TM) to the provider. In other words, it is the transacted (as opposed to list) price. **Out-of-pocket spending** is the amount owed by the enrollee (i.e. the sum of any coinsurance, copay, and deductible). For individuals enrolled in TM, some of this "out of pocket" spending may be covered by supplemental private insurance (Medigap), which they may purchase separately.

Medical spending is divided across claims files based on who is billed, which does not map perfectly to our concept of "place of care." In particular, institutional billing goes to the relevant institutional file (e.g., inpatient or outpatient) while individual provider billing (regardless of whether it is inpatient or outpatient) goes to the physician (aka carrier) file. The structure of claims files is slightly different across the two data sources. We use three HCCI claims files: Inpatient, outpatient and physician. We use seven CMS claims files: inpatient, outpatient, physician, SNF, home health, durable medical equipment, and hospice. In HCCI, the SNF spending is in the inpatient file; we identify SNF claims in the HCCI inpatient file based on their Place of Service (POS) codes (POS code of 31-33 determines a SNF). In HCCI, home health and durable medical equipment are in the outpatient and physician files. Hospice is reimbursed by TM for both TM and MA enrollees; there is therefore no hospice spending in the HCCI data, but we can observe hospice spending in the CMS data for both TM and MA enrollees. Finally, we note that in HCCI the inpatient file includes all admissions in 2010, while in CMS the inpatient and SNF files include discharges in 2010; we therefore supplement the 2010 SNF and inpatient discharge files in CMS with the 2011 SNF and inpatient discharge files, and in both files limit the analysis to admissions that occur in 2010; in this way we reconstruct a 2010 admission file that is parallel to the HCCI admission file.

Below we describe he construction of specific variables.

Total spending and components All of these measures are constructed at the enrollee-month level unless explicitly noted otherwise. Note that for inpatient and SNF spending, we associate the spending with the month in which the admission occurred even when the stay extends into subsequent months.

- **Total spending:** the sum of inpatient, outpatient, and SNF spending.
- **Inpatient spending:** in the CMS data it covers all spending on the inpatient file plus spending on the physician file associated with an inpatient hospital (POS code of 21). In the HCCI data it covers all spending on the inpatient file minus SNF spending (as mentioned, POS codes of 31-33) plus spending on the physician file associated with an inpatient hospital (POS code of 21).
- **Outpatient spending**: in CMS data it is the sum of all spending on the outpatient file, the home health file, and the durable medical equipment file, plus all spending on the physician file for which POS is not 21. In HCCI data is it the sum of all spending on the outpatient file (which, recall, includes home health and durable medical equipment), plus spending on the physician file for which POS is not 21.
- **SNF spending:** in CMS data it is the sum of all spending on the SNF file, while in HCCI file it is the sum of all spending on the inpatient file with POS codes 31-33.
- **Hospice spending**: hospice care is reimbursed by TM for both TM and MA enrollees. There is therefore no hospice spending in the HCCI data, but we can observe hospice spending in the CMS data for both TM and MA enrollees. We use the hospice file in the CMS data to measure hospice spending in TM and in MA.

Healthcare utilization In addition to measuring spending, we also measure healthcare utilization. We define a number of standard measures of healthcare use for each enrollee-month. We measure inpatient utilization using the inpatient files. In the HCCI data we only count observations that are inpatient hospital admissions (i.e. we exclude SNF admissions based on POS codes of 31-33). We measure SNF utilization using the SNF file in the CMS data and the inpatient file in the HCCI data, only counting admissions with POS codes of 31-33.

- **Inpatient days:** the sum of the days associated with each inpatient admission that month; as with our inpatient spending measure, this will include all the days for each admission in a given month, even if those days extend beyond that month. We measure the days of a given admission as the difference between discharge date and admission date, plus 1.
- **SNF days:** is defined analogously to inpatient days. In the CMS file, discharge date is missing for about 18 percent of the observations, which appears to reflect discharges that extend beyond the 100-day coverage period for SNF in TM. Since we are interested in TM-covered utilization, we impute 100 days for such discharges.
- **Inpatient admissions:** any inpatient admission that month.[20]
- **Physician visits:** is measured based on claims in the physician file (excluding claims with POS code of 21, which indicates that they occur in an inpatient setting). We define physician visits as the sum of **primary care visits** and **specialty care visits**. We allow a maximum of one primary care visit per patient-day, and one specialist visit per patient day. Following the approach in Finkelstein et al. (2016), our definition of primary care physicians and specialists follows the Dartmouth Atlas.[21] Specifically, we crosswalk the primary care and specialist definitions in the Dartmouth Atlas to the list of HCFA specialty codes in the CMS data. The HCCI data has a separate set of provider category codes which we crosswalk to the HCFA specialty codes.
- **ED visits:** we identify ED visits based on their revenue center codes. ResDAC identifies revenue center codes 0400-0459 and 0981 as indicating ER serivces.[22] We define ED visits as the sum of **outpatient ED visits** and **inpatient ED visits.** We allow a maximum of one outpatient ED visit per patient-day and a maximum of one inpatient ED visit per patient - admission date. We identify an outpatient ED visit by an outpatient claim line with the relevant revenue code and identify an inpatient ED visit by a (non-SNF) inpatient claim line with the relevant revenue code.

[20] We do not define an analagous "SNF admission" measure because the HCCI data are not conduicive to defining distinct admissions; we observe many consecutive short stays in SNFs for patients, and it is unclear whether these are distinct admissions.

[21] See http://www.dartmouthatlas.org/downloads/methods/research_methods.pdf, page 6

[22] Source: https://www.resdac.org/resconnect/articles/144.

- **Diagnostic Tests and Imaging Procedures.** Our definition of diagnostic tests and imaging procedures follows Song et al. (2010), and is based on BETOS codes: codes beginning with T are diagnostic tests, and codes beginning with I are imaging procedures. We examine all claims files for possible diagnostic tests and imaging procedures.
- **Surgery.** We define surgeries as the sum of **inpatient surgeries** and **outpatient surgeries.** We define an **inpatient surgery** using the inpatient claims file (excluding, in the case of the HCCI data, POS codes of 31-33 since these indicate SNF). We classify an inpatient admission as having an inpatient surgery if it is associated with a "surgical DRG".[23] We count each unique inpatient admission with a surgical DRG as one inpatient surgery. We define an **outpatient surgery** based on the HCPCS codes in the outpatient file explicitly identified as corresponding to "outpatient surgery"; we exclude any claims classified as "emergency room" claims from this definition. We restrict to a maximum of one outpatient surgery per patient-date.

Spending per encounter To measure spending per SNF day we use the above definitions of SNF spending and SNF days. To measure spending per inpatient admission or inpatient day, we use the above definition of inpatient admissions and inpatient days above; we measure inpatient spending however only counting spending on the inpatient file (i.e. not including physician spending with POS code of 21 as we do when breaking down spending by category). To measure spending per outpatient ED visit; we count all spending on the same date as the outpatient ED visit date that is on the outpatient file or is on the physician file with a POS code of 23 ("Emergency room"). For all of these measures, we take the average across enrollee months of the ratio of spending to utilization for that enrollee-month..

Preventive care We analyze the set of preventive care measures in Finkelstein et al. (2016) that we can reasonably replicate in our data. These in turn are drawn from procedures measured in the Dartmouth Atlas and the Centers for Medicare and Medicaid (CMS). These measures are typically defined as rates of any care receipt during an observation period (an enrollee-month in the baseline analysis) for a denominator of "relevant" patients. In some cases, we have to modify the denominator due to limitations of the HCCI data (e.g. coarse age bins or the inability to do a two-year "look back" period). We highlight these modifications below, which we do in parallel for both MA and TM measures so that they are internally comparable:

- **Mammogram** is defined following the Dartmouth Atlas (see http://www.dartmouthatlas.org/data/table.aspx?ind=169). We define the denominator as women ages 65-74; due to the coarse-

[23] The primary source was https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/MedicareFeeforSvcPartsAB/downloads/DRGDesc10.pdf. Information on 6 DRGs (14, 16, 17, 570, 571, 572), which is not present in the above source, was added from https://www.cms.gov/Medicare/Coding/ICD10/Downloads/ICD-10-MS-DRG-v32-Definitions-Manual-Text.zip. Information on DRG 15 was added after manual search on-line.

ness of the age variable in HCCI, this is a broader "risk set" than the Dartmouth Atlas denominator of women ages 67-69.

- **Diabetes screen** ("HbA1c test"), **cholesterol test** ("blood lipids test"), and **retinal eye exam (**"retinal or dilated eye exam") are defined following the Dartmouth Atlas (see http://www.dartmouthatlas.org/data/map.aspx?ind=160). For all of them the denominator (risk set) is defined as all enrollees aged 65-74 with a diagnosis of diabetes. Due to the coarseness of the age variable in HCCI, this is a slightly different "risk set" than the Dartmouth Atlas denominator of enrollees aged 65-75 with a diagnosis of diabetes. The definition of "a diagnosis of diabetes" also differs because we have only one year of data while the Dartmouth Atlas defines a diabetes diagnosis based on encounters with specific codes identifying diabetes during the year or prior year; we are able to replicate their coding exactly, but because we can only look during our one observation year, our definition is more stringent than theirs.

- **Seasonal influenza vaccine, cardiovascular screening blood test, colorectal cancer screening, pap smears, pelvic examinations,** and **prostate cancer screening** are defined following CMS' preventive care definitions (see https://www.cms.gov/Medicare/Prevention/PrevntionGenInfo/ Downloads/MPS_QuickReferenceChart_1.pdf; downloaded on 08/11/2016); for a list of relevant ICD-9 codes see https://www.cms.gov/Medicare/Prevention/ PrevntionGenInfo/Downloa QuickReferenceChart-1TextOnlywithICD9.pdf (downloaded on 08/11/2016). For influenza, cardiovascular screening, and colorectal cancer, the denominator is everyone. For pap smears and pelvic exams, the denominator is all women, and for prostrate cancer the denominator is all men.

Appropriateness of ED visit: Billings et al. Algorithm We also classify visits using an algorithm developed by Billings et al. (2000) that is based on the primary ICD-9 diagnosis code for the visit. To construct this algorithm, a panel of emergency department and primary care physicians was given access to a sample of 6,000 full emergency department records. These full records contained detailed information about the patient including age, gender, vital signs, medical history, presenting symptoms and also information about the resources used on the patient in the emergency department, the diagnoses made and procedures performed. Based on this much more extensive information than available in typical discharge or claims data like ours, each physician classified each record into one of four categories. For each primary diagnosis, the algorithm assigns probabilities to each category of visit, based on averaging all the physicians' codings across all visits with that diagnosis. This reliance on probabilities derived from *ex post* diagnoses rather than *ex ante* symptoms is one of the major limitations of this measure, as has been noted elsewhere (e.g., Raven et al. 2013).

Several subsequent studies have validated the algorithm (e.g. Ballard et al., 2010, Gandi and Sabik 2014). Although originally created with ED discharge data, it has been applied to classify ER visits from TM claims data (Joynt et al., 2013), and we follow that approach here. Like Joynt et al. (2013), we exclude from our analysis the few (in our case, less than 4 percent in either TM or MA data) ED visits with multiple primary diagnoses.

The algorithm classifies ED visits into 4 mutually exclusive categories. The fist distinction is between **non-emergent** and **emergent** cases. A non-emergent case is one where care is not required within 12 hours (for example, a toothache). Among emergent cases, a distinction is then made between **emergent, ED care needed** and **emergent, ED care not needed ("primary care treatable");** the latter refers to cases where care is needed within 12 hours but can be provided in a primary care setting (e.g. a lumbar sprain). Finally, among emergent cases where ED care is needed, the algorithm makes a final distinction between those that are "**emergent, but primary care preventable"** and those that are "**emergent but not primary care preventable."** This final classification distinguishes between emergencies that require ED care but could have been prevented with appropriate ambulatory care (e.g. a heart attack) and those that could not.

Finally, diagnoses are marked as "unclassified" if the algorithm does not assign a probability weight to it. Presumably these represent diagnoses that are too infrequent to have been included in the dataset of visits coded by the panel of physicians who created the algorithm. In our setting, we find that about a quarter of ED visits are unclassified by the algorithm; this is comparable to what has been found in other settings (e.g. Taubman et al. 2014).

Appendix C: Analysis of inpatient prices

Our objective is to compare the price of an admission at a given hospital for a given diagnosis (DRG) in MA to what this price would have been if (counterfactually) that admission had occurred under TM. For this analysis, we make two departures from our baseline. First, in measuring inpatient spending, we now only consider spending on the inpatient file, and not spending on the physician file associated with the inpatient admission (as we did previously in analyzing inpatient spending in e.g. Table 4). Second, we limit our analysis to the approximately 4,000 hospitals in our baseline MA sample that, for purposes of TM reimbursement, would have been covered by Medicare's Prospective Payment System (PPS). PPS covers virtually all standard (non-specialty) hospitals; limiting ourselves to MA admissions in these hospitals excludes about 5 percent of inpatient admissions, and about 7 percent of payments to inpatient hospitals. For these standard hospitals, pricing in TM (and to the best of our understanding in MA), is based primarily on the hospital at which the admission occurs and the DRG for which the patient was admitted.

We conduct two analyses, an analysis of average price differences by state, and an analysis of average price differences by DRG (for common DRGs). They are conceptually the same, just created at different units of aggregation.

State-level prices. To arrive at a state-level average price (in either MA or TM), we calculate the average price in the state for each MA admissions in a given DRG, and then take a weighted average of prices for each DRG in the state. We use as weights the DRG's (national) share of admissions in MA;[24] differences in average prices within MA (or within TM) across states therefore

[24] For a few small states, there are a number of common (national) DRGs which, in that state, have no admissions.

reflect price differences for a common “DRG basket.”

Measuring the MA price for each MA admission is straightforward: we simply calculate total payments to hospitals for that admission, as measured in the inpatient file.

Measuring the (counterfactual) TM price for each MA admission proceeds in two steps. First, we calculate the TM formula price for each MA admission as a function of the hospital and DRG for that admission.[25] We compute the average, TM formula price for each DRG in the state, and then construct the state average TM formula price by taking a weighted average of prices across DRGs, using each DRG’s (national) share of admissions (in MA) in that DRG as weights.

Second, we adjust these state average TM formula prices for observed differences between the state-level transacted price and formula price in TM. The actual, transacted TM price will not always correspond exactly to the formula TM price. For example, in certain costly cases, hospitals receive additional “outlier payments” covering 80 percent of costs beyond a threshold. In addition, if the individual is transferred to another hospital, the actual reimbursement will be below the reimbursement formula. Since in MA we observe transacted prices, we want to compare to an estimate of TM transacted prices. We therefore adjust the TM formula price to account for the average difference between TM actual and TM formula price. We calculate this adjustment factor using CMS data in which we can observe actual TM prices (i.e. payments, as we do in MA data) and can also construct TM formula prices. We calculate a state-specific adjustment factor that is the ratio of actual TM prices to formula TM prices in that state.[26] We multiply the state’s average TM formula price by this state-specific adjustment factor to arrive at our estimate of the state-specific average TM price. Appendix Table A3 shows the state-specific average MA and TM prices.

To address this, we impute the national average price for that DRG in that missing state-DRG pair, corrected by a state-specific correction factor. The state-specific correction factor is given by the ratio of the state price and average national price for the DRGs we do observe in that state.

[25] As noted, under TM, these admissions would be reimbursed by Medicare’s PPS; the PPS reimbursement formula is the product of a hospital-specific “base payment” rate times a diagnosis-specific (DRG) weight; both are publicly available from CMS.The DRG weights can be found here: https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Acute-Inpatient-Files-for-Download-Items/CMS1247873.html (see file FY_2010_FR_Table_5). The hospital base payment rates can be found in the Medicare Impact File (available here: https://www.cms.gov/Medicare/Medicare-Fee-for-Service-Payment/AcuteInpatientPPS/Historical-Impact-Files-for-FY-1994-through-Present.html). The base payment rates for the hospital include hospital-specific adjustments for wage index reclassifications, indirect medical education payments, and disproportionate share payments. The HCCI data has encrypted hospital identifiers that can not be directly mapped to the publicly available data on hospital base payment rates. We are extremely grateful to Zack Cooper for providing us with a file containing these base payment rates linked to the encrypted hospital identifiers.

[26] Once again, for both actual and formula TM prices, we compute the average of admission prices by state-DRG, and then a weighted average by state, in which the weight associated to each DRG is the national share of MA admissions with that DRG.

DRG-level prices. The DRG-level analysis proceeds in a similar manner except that we now compute the average price for each DRG by taking a weighted-average of prices for each state in the DRG, using as weights the state's share of admissions (across all DRGs) in MA; the differences in average prices across DRGs within MA (or within TM) therefore reflects price differences for a common "state basket," which mimics the geographic distribution of MA admission across states.

The measurement of the average TM price for each DRG proceeds in the same two steps. First, we calculate each DRG's average TM formula price using the same TM formula prices for each admission that we used in the state-level analysis, but now average these across states for each DRG, using the state's share of admission (in MA) as weights. Second, we adjust the average TM formula price in the DRG by a DRG-specific adjustment factor reflecting the DRG-specific ratio of actual TM prices to formula TM prices.[27] Appendix Table A2 shows the DRG-specific average MA and TM prices for the 20 most common DRGs.

Appendix References

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Gandhi, Sabrina and Linsday Sabik. 2014. "Emergency Department Visit Classification Using the NYU Algorithm." *The American Journal of Managed Care* 20(4): 315-320.

Joynt, Karen, Atul Gawande, E. John Oray and Ashish Jha. 2013. "Contribution of Preventable Acute Care Spending to Total Spending for High-Cost Medicare Patients." *Journal of the American Medical Association* 309(24): 2572-2578.

Raven, M.C., R.A. Lowe, J. Maselli, and R.Y. Hsia. 2013. "Comparison of presenting complaint vs discharge diagnosis for identifying 'nonemergency' emergency department visits." *Journal of the American Medical Association* 309, 1145-1153.

[27] For both actual and formula TM prices, we compute the average admission prices for each state-DRG, and then a weighted average by DRG, in which the weight associated with each state is the state's share of MA admissions.

Appendix Figure A1: States included in the baseline sample

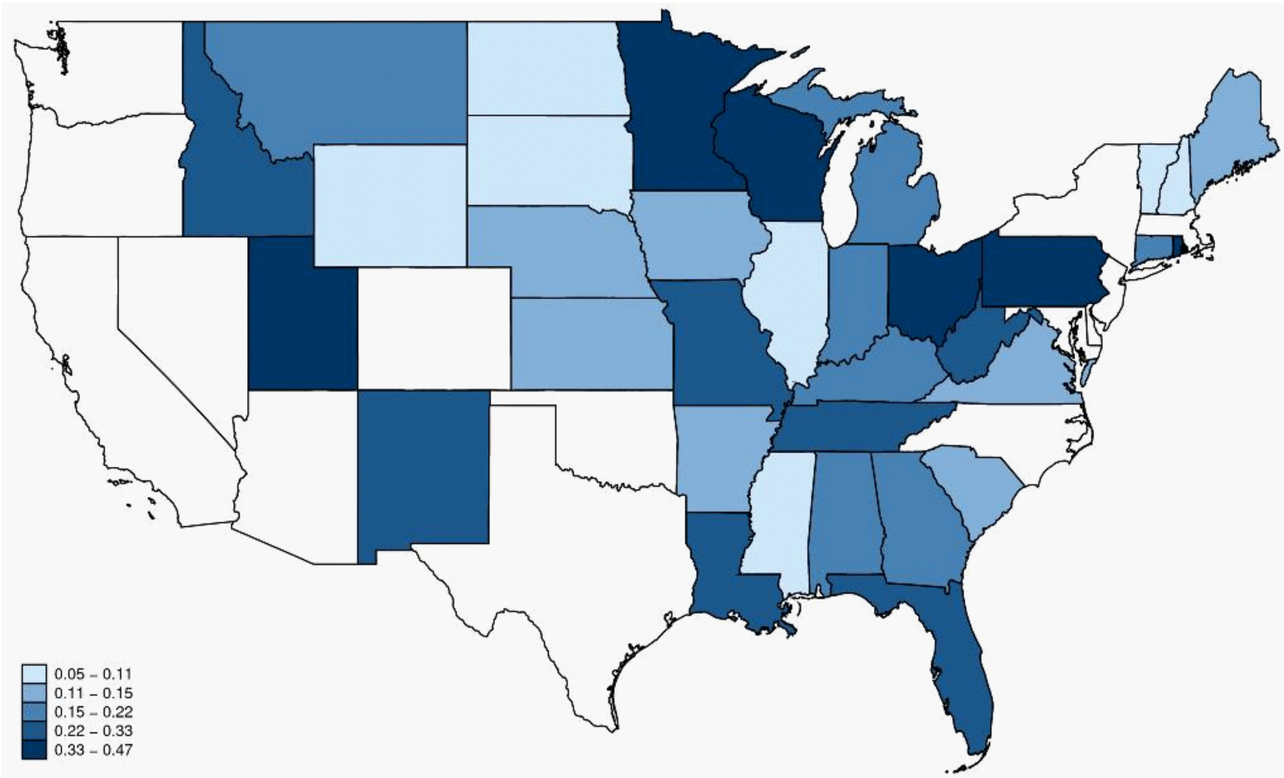
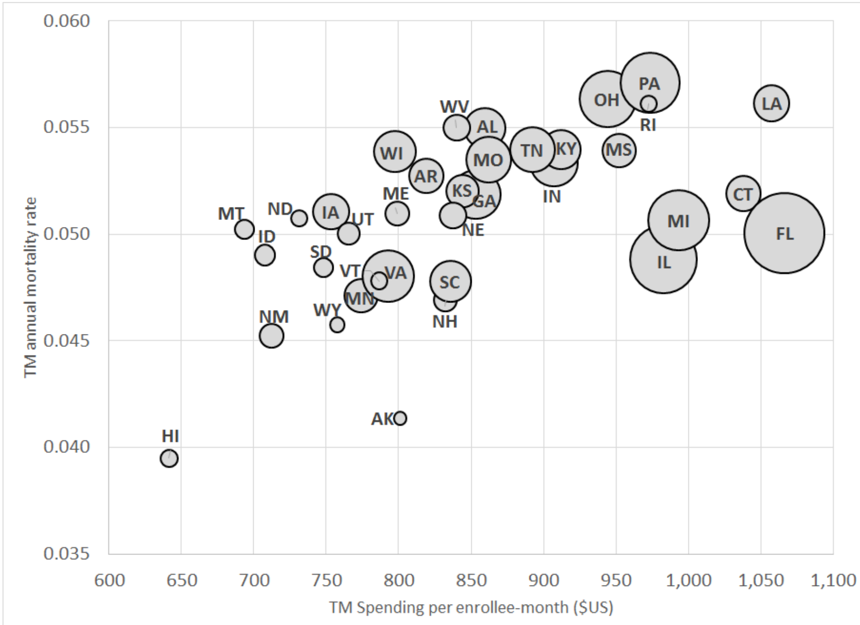


Figure shows MA share of Medicare enrollment by state; states that are white are omitted from baseline sample. Appendix A and Appendix Table A1 provide more detail.

Appendix Figure A2: Mortality-Spending Relationship in TM and MA



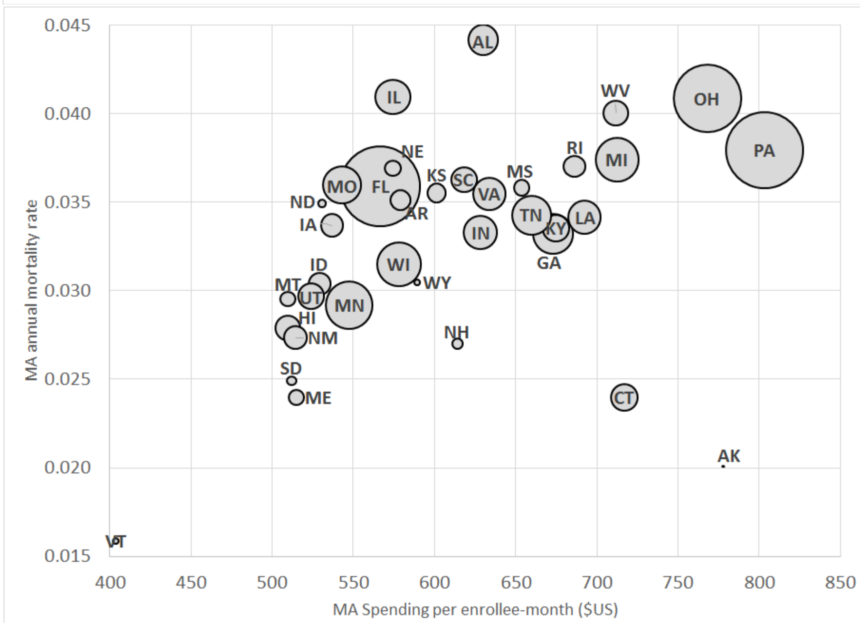


Figure shows relationship between annual mortality rate and spending for each state, separately for TM (top panel) and MA (bottom panel). In the top panel, the size of each bubble is proportional to the number of TM enrollees in the state. In the bottom panel, the size of each bubble is proportional to the number of MA enrollees in the state.

Appendix Figure A3: Propensity score distributions

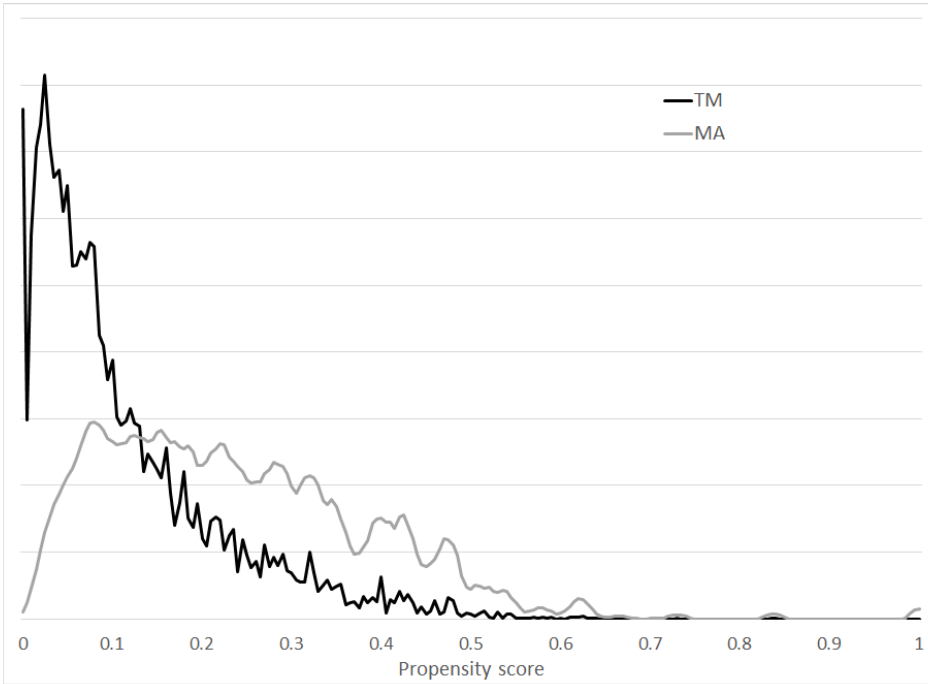


Figure shows the distribution of propensity scores in the baseline sample for the TM (black) and MA (gray) populations. The figure uses row 3 of Table 9, where propensity scores are generated from a logit regression of an MA indicator on dummy variables for each risk score bin (of 0.1), which is estimated county by county.

Appendix Table A1: Construction of baseline sample

	MA Share (%)	HCCI insurers share of MA (%)	Counts of Enrollee-Months in HCCI Insurers			
			All HCCI	All CMS	cleaned CMS	% Difference: ((3) - (5))/(5)
	(1)	(2)	(3)	(4)	(5)	(6)
All	28.0	37.4	32,505,844	44,371,265	41,684,486	-22.0
AL	**22.4**	**28.2**	**421,380**	**449,306**	**383,695**	**9.8**
AK	**0.8**	**58.6**	**2,602**	**2,680**	**2,631**	**-1.1**
AZ	39.2	53.9	648,500	1,807,922	1,628,786	-60.2
AR	**14.5**	**43.3**	**272,328**	**285,038**	**284,887**	**-4.4**
CA	42.9	22.6	642,277	4,169,255	4,071,737	-84.2
CO	39.2	47.9	354,798	1,076,124	1,013,937	-65.0
CT	**21.5**	**20.9**	**210,161**	**236,303**	**194,975**	**7.8**
DE	3.8	72.0	39,199	37,995	35,596	10.1
DC	13.6	12.4	6,317	10,271	5,019	25.9
FL	**32.8**	**56.6**	**5,097,850**	**6,019,462**	**5,458,355**	**-6.6**
GA	**24.4**	**69.1**	**1,739,812**	**1,821,869**	**1,729,667**	**0.6**
HI	**49.1**	**23.1**	**151,329**	**220,785**	**153,906**	**-1.7**
ID	**33.0**	**37.9**	**244,680**	**266,744**	**259,697**	**-5.8**
IL	**11.1**	**59.7**	**1,094,149**	**1,119,609**	**1,091,129**	**0.3**
IN	**18.2**	**47.4**	**784,123**	**795,364**	**778,536**	**0.7**
IA	**14.7**	**61.5**	**444,714**	**455,813**	**454,166**	**-2.1**
KS	**12.3**	**61.1**	**300,774**	**306,948**	**302,071**	**-0.4**
KY	**18.2**	**60.9**	**685,965**	**696,447**	**696,236**	**-1.5**
LA	**28.0**	**57.2**	**932,542**	**953,417**	**935,861**	**-0.4**
ME	**15.6**	**25.0**	**87,411**	**90,216**	**90,087**	**-3.0**
MD	9.3	27.9	180,940	183,320	154,445	17.2
MA	25.4	8.2	140,131	194,537	103,079	35.9
MI	**18.5**	**16.2**	**446,674**	**453,679**	**444,670**	**0.5**
MN	**49.8**	**9.2**	**321,824**	**340,132**	**340,008**	**-5.3**
MS	**10.0**	**49.2**	**197,121**	**205,978**	**205,846**	**-4.2**
MO	**24.6**	**46.7**	**999,750**	**1,037,740**	**999,320**	**0.0**
MT	**19.9**	**54.6**	**166,173**	**173,636**	**173,559**	**-4.3**
NE	**13.0**	**68.1**	**230,020**	**237,516**	**235,717**	**-2.4**
NV	36.0	87.9	337,836	1,021,319	1,020,570	-66.9
NH	**8.5**	**35.1**	**56,321**	**57,540**	**57,242**	**-1.6**
NJ	14.4	60.1	706,632	1,060,082	1,028,209	-31.3
NM	**30.0**	**20.6**	**142,307**	**169,552**	**148,360**	**-4.1**
NY	35.9	14.6	539,254	1,405,315	1,270,208	-57.5
NC	19.5	53.5	1,324,226	1,401,748	1,138,093	16.4
ND	**9.0**	**59.9**	**54,576**	**57,067**	**57,052**	**-4.3**
OH	**39.4**	**57.0**	**3,856,644**	**3,957,898**	**3,855,415**	**0.0**
OK	16.8	46.9	183,566	428,148	416,256	-55.9
OR	47.8	15.1	205,505	416,014	401,139	-48.8
PA	**43.1**	**18.4**	**1,539,253**	**1,676,370**	**1,583,624**	**-2.8**
RI	**44.2**	**44.4**	**302,571**	**308,224**	**283,232**	**6.8**
SC	**16.5**	**36.3**	**396,921**	**409,194**	**408,879**	**-2.9**
SD	**9.0**	**69.2**	**78,564**	**82,584**	**82,534**	**-4.8**
TN	**26.9**	**48.0**	**1,086,782**	**1,192,598**	**1,073,406**	**1.2**
TX	21.6	52.6	1,478,223	3,092,452	2,753,984	-46.3
UT	**38.8**	**51.4**	**480,772**	**517,799**	**500,744**	**-4.0**
VT	**5.1**	**56.9**	**29,216**	**29,260**	**29,244**	**-0.1**

All data except from column (3) are from CMS. Columns (1) and (2) show the MA share of total Medicare enrollment and the HCCI insurers' share of MA enrollment, respectively. Columns (3) through (5) show counts of enrollee-months in the HCCI insurers in different data sets. Columns (3) and (4) are based on the full sample of data (see columns (7) and (3) of Table 1, respectively). Column (5) excludes enrollees in SNP plans. States that are in bold are those that are included in our baseline sample (using our criteria of being within 10%), and correspond to columns (8) and (6) of Table 1, respectively.

Appendix Table A2: MA-TM prices differences for most common DRGs

DRG Code (1)	DRG Description (2)	MA Admissions (3)	MA price (4)	TM price (5)	(MA-TM)/TM (6)
All DRGs (weighted by MA admission shares)		488,008	10,054	9,945	1.1%
470	Major Joint Replacement Or Reattachment Of Lower Extremity W/O Mcc	23,879	12,387	12,005	3.2%
392	Esophagitis, Gastroent & Misc Digest Disorders W/O Mcc	10,897	4,203	4,328	-2.9%
871	Septicemia Or Severe Sepsis W/O Mv 96+ Hours W Mcc	10,035	11,490	11,540	-0.4%
291	Heart Failure & Shock W Mcc	9,595	8,917	9,009	-1.0%
292	Heart Failure & Shock W Cc	9,113	5,939	6,075	-2.2%
312	Syncope & Collapse	8,032	4,255	4,476	-4.9%
690	Kidney & Urinary Tract Infections W/O Mcc	8,024	4,544	4,729	-3.9%
194	Simple Pneumonia & Pleurisy W Cc	7,488	6,017	6,049	-0.5%
310	Cardiac Arrhythmia & Conduction Disorders W/O Cc/Mcc	7,185	3,513	3,495	0.5%
247	Perc Cardiovasc Proc W Drug-Eluting Stent W/O Mcc	6,710	11,865	11,510	3.1%
313	Chest Pain	6,682	3,182	3,381	-5.9%
190	Chronic Obstructive Pulmonary Disease W Mcc	6,599	7,021	7,238	-3.0%
378	G.I. Hemorrhage W Cc	6,396	6,010	6,098	-1.4%
287	Circulatory Disorders Except Ami, W Card Cath W/O Mcc	6,291	6,351	6,387	-0.6%
641	Nutritional & Misc Metabolic Disorders W/O Mcc	6,129	4,155	4,255	-2.3%
193	Simple Pneumonia & Pleurisy W Mcc	5,682	8,670	8,717	-0.5%
192	Chronic Obstructive Pulmonary Disease W/O Cc/Mcc	5,508	4,300	4,355	-1.3%
191	Chronic Obstructive Pulmonary Disease W Cc	5,424	5,724	5,835	-1.9%
683	Renal Failure W Cc	5,395	6,197	6,391	-3.0%
65	Intracranial Hemorrhage Or Cerebral Infarction W Cc	5,176	6,967	7,051	-1.2%

Table reports average prices for a hospital admission in TM and MA for the top 20 DRGs, and overall across all DRGs (not limited to the top 20). Averages are computed for each DRG using a common (MA) "basket" of state admission shares. Sample is a subset of our baseline sample; it is limited to all MA inpatient admissions to hospitals that are paid (by CMS) under prospective payment system (PPS).

Appendix Table A3: MA-TM price differences, by state

State (1)	MA Admissions (2)	MA price (3)	TM price (4)	(MA-TM)/TM (5)
AL	9,411	8,984	8,862	1.4%
AR	4,733	9,461	9,056	4.5%
CT	2,894	11,495	12,778	-10.0%
FL	104,424	10,291	9,851	4.5%
GA	27,876	10,300	9,944	3.6%
HI	1,351	13,275	13,350	-0.6%
IA	5,925	9,656	9,693	-0.4%
ID	2,189	10,297	9,700	6.2%
IL	19,359	10,183	10,356	-1.7%
IN	11,953	9,703	9,522	1.9%
KS	5,261	9,428	9,533	-1.1%
KY	13,794	9,684	9,733	-0.5%
LA	20,905	9,948	9,841	1.1%
ME	996	10,341	10,869	-4.9%
MI	8,674	10,097	10,948	-7.8%
MN	5,264	10,911	10,969	-0.5%
MO	17,550	9,657	9,594	0.7%
MS	4,033	9,728	9,446	3.0%
MT	2,133	9,777	9,512	2.8%
ND	719	9,532	9,230	3.3%
NE	3,998	10,215	10,319	-1.0%
NH	591	11,229	11,010	2.0%
NM	1,748	10,949	11,198	-2.2%
OH	89,716	9,574	9,916	-3.5%
PA	35,344	11,130	10,401	7.0%
RI	5,149	11,575	12,144	-4.7%
SC	6,800	10,003	10,376	-3.6%
SD	1,073	10,831	10,802	0.3%
TN	24,161	9,756	8,959	8.9%
UT	6,112	9,638	9,363	2.9%
VA	14,409	9,773	9,908	-1.4%
VT	146	11,936	13,690	-12.8%
WI	19,099	10,334	10,521	-1.8%
WV	9,834	9,238	9,647	-4.2%
WY	350	12,930	13,034	-0.8%

Table reports average prices for a hospital admission in TM and MA for each state in our baseline sample (except Alaska which is omitted because it had too few inpatient admissions for us to report). Averages are computed for each state using a common (MA) "basket" of DRG admission shares. Sample is a subset of our baseline sample; it is limited to all MA inpatient admissions to hospitals that are paid (by CMS) under prospective payment system (PPS).