Defining Disease Episodes and the Effects on the Components of Expenditure Growth*

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Abstract

To better understand productivity and inflation in the health sector, health economists have advocated tracking the cost of treatment by disease over time. However, there are several methods for measuring the cost of treatment, and little work has been done to understand how different approaches affect disease-price inflation. In this paper we compare various methodologies for allocating expenditures to disease episodes and their effect on disease-price inflation for a sample of commercially-insured individuals over the 2003 to 2007 period. We find that the selected allocation method impacts inflation rates, but the annual growth rate stays within the range 2.9 to 3.9 across a variety of methods. The paper highlights various issues and trade-offs that may be useful when selecting among the different approaches.

*The views expressed in this paper are solely those of the authors and do not necessarily reflect the views of the Bureau of Economic Analysis, the Federal Reserve Bank of San Francisco, or the Board of Governors of the Federal Reserve System.

1 Introduction

The goal of health care spending is to treat diseases and improve health, yet there are no national health statistics that track the cost of treatment by disease. The need for more detailed statistics has been recognized by both academics and policy makers, who have called for the development of a National Satellite Account for Health Care that is centered around the cost of disease treatment.[1] There are many reasons for focusing on the cost of disease treatment and, in particular, the growth in the cost of disease treatment. Policy makers, consumers, and industry participants are increasingly interested in whether changes in the cost of treatment are worth the health benefit. By focusing on spending by disease rather than by service, researchers will be better able to connect expenditures for specific diseases with the associated health outcomes. Tracking disease expenditures also provides a more relevant unit of price for patients, since patients ultimately seek treatment for a disease, regardless of the point of service (e.g., physician office, clinic or hospital).[2] Indeed, changes in technologies and practice patterns often lead to important shifts in treatment that drive a wedge between the price of disease treatment and the price of the service (e.g., shifts from hospital inpatient to outpatient services tends to lower the price of treatment, but does not affect the price of the services). Moreover, recent health care reforms have led to shifts in payment structures, away from paying a fee for each service and toward bundled payments that pay for the total cost of treating a disease.

There is general agreement that tracking disease-price inflation is valuable, but there is little consensus regarding how a "disease-price" should be defined and measured. Although several papers look at disease-price growth, they typically focus on only one disease allocation method (e.g., Aizcorbe and Nestoriak (2011), Roehrig and Rousseau (2011), Dunn et al. (2012), Dunn et al. (2013), and Bradley (2013)). Those papers that do compare allocation methods typically look at the amount allocated to disease categories (e.g., Rosen et al. (2012), and MaCurdy (2009)), such as the allocation of expenditures to heart disease and diabetes. However, the current literature has not examined how the different approaches for allocating disease expenditures might affect disease-price growth.[3] Understanding how these different measures might affect disease-price growth has implications for measuring inflation and productivity in the health sector.

To help understand the effect of disease-price measurement on inflation, this paper analyzes various methods for allocating expenditures to diseases using commercial claims data from MarketScan for the years 2003 to 2007 that

[1] See Berndt et al. (2000), Rosen and Cutler (2007), National Research Council (2010), and Aizcorbe et al. (2012a).

[2] Current national price statistics track the prices of specific services, regardless if treatment patterns change.

[3] One recent working paper on this topic is Hall and Highfill (2013), which focuses on the Medicare population using survey data.

includes millions of enrollees in each year. There are two primary aims of this paper: (1) provide a range of estimates for disease-price inflation; and (2) provide some basic guidelines for how the selected methodology may affect the measurement of disease-price inflation. There are two key advantages to focusing on a larger sample. First, a larger sample is likely to be more representative of high-spending individuals that may not be present in smaller surveys (Aizcorbe et al. (2012b)). Second, the larger sample will create precisely measured estimates, which ensures that the differences in the estimates across approaches are not driven by imprecision.[4]

We find that the different methodologies produce a range of estimates for disease-price inflation from 12.3 percent (CAGR 2.9) to 16.5 percent (CAGR 3.9), with the average growth rate of about 15 percent (CAGR 3.5) across methods. Although 15 percent is the average among the selected measures, taking the average is not necessarily the best approach for selecting a disease-price index. As discussed in the text, the best approach may depend greatly on the particular application and the goals of the researcher. Looking at our range of estimates, we find that between 50 to 68 percent of the growth in expenditures may be attributed to disease-price growth.

The paper is organized as follows. Section 2 of this paper provides a discussion of different grouper methodologies. Section 3 discusses how the indexes are measured. Section 4 presents the overall results followed by a discussion of the methodologies in section 5. Section 6 concludes.

2 Methods for Disease Expenditure Allocation

A major challenge for assigning expenditures to a disease episode is that individuals may have multiple diseases. For example, if a patient visits a doctor's office to treat both hypertension and heart disease, how should the expenditures from that visit be allocated across these two diseases? This problem is substantial in health care markets in general, and is also present in the commercially-insured sample studied in this paper. In our data, we find that individuals with more than two conditions account for 97 percent of total expenditures. In fact, most expenditures are on patients that have many conditions, with 53 percent of expenditures allocated to those with seven or more conditions.

Another challenge is determining the level of aggregation to use when allocating expenditures to mutually exclusive disease categories. One could use very broadly defined disease categories, such as the Major Diagnostic Categories, which include just 25 diseases. Alternatively, one could use the highly disaggregate categories contained in the International Classification of Diseases 9th edition (ICD-9) that includes about 13,000 disease definitions. Precisely

[4] Dunn et al. (2012) show that the standard errors on inflation estimates using large claims data tend to be very small.

defined disease categories are useful to account for the heterogeneity in individual conditions. However, the more granularity in each disease episode category, the fewer individuals will fall into each category, potentially reducing the precision of the estimates. As discussed in more detail later in this paper, there are a variety of possible categorizations, and the appropriate categorization may depend on the application and data.

Following the discussion of Rosen and Cutler (2012), we focus on three general approaches for allocating expenditures. The first approach is an encounter-based methodology, which assigns expenditures to diseases based on the observed diagnosis at the claim line. A second approach is an episode-grouper approach, which uses software algorithms to review a patient's medical history and assign claim lines to distinct episodes. These algorithms rely on the medical expertise incorporated into the programs. Episodes include all services involved in diagnosing, treating and managing medical conditions and potentially have varying lengths of time, which end when treatment has completed. The third approach is a person-based approach, which uses regressions and the characteristics of the patient in an attempt to statistically divide expenditures across disease categories. Although there are three main approaches analyzed in this paper, there are a variety of ways that each approach may be executed that may impact both the allocation across diseases and the measure of disease-price inflation. The following subsection describes each approach in more detail.

2.1 Encounter-based Approach

The encounter-based methodology uses the listed diagnosis on the claims to assign expenditures to diseases. One advantage of this approach is that it is easy to apply, since one only needs the observed diagnosis on the claim record. There are two main disadvantages. First, when there are comorbidities, the allocation of expenditures is decided entirely by the first listed diagnosis. This may not reflect an accurate allocation of services for an individual with both heart disease and diabetes, where the presence of diabetes may lead to significantly greater complications for the heart disease treatment. A second complication is that if a diagnosis is not listed, as is common with prescription drug claims information, then those expenditures are not assigned to any disease.

When applying an encounter-based approach one of the main choices is to determine the level of disease aggregation and also which diagnosis to look at. The diagnosis observed on the claims records are ICD-9 codes, which include thousands of distinct diagnosis categories. Each claim line record could also have multiple diagnoses listed on a single claim. For both of these choices, we follow the standard approach used in the literature, which was

recently applied by Roehrig and Rousseau (2011). Specifically, we use the first listed diagnosis on the claim record, known as the primary diagnosis, which is the patient's major illness for an encounter. Rather than using the highly disaggregate ICD-9 diagnosis, we use the categories defined by the Clinical Classification Software (CCS), a free application developed by Agency for Healthcare Research and Quality (AHRQ) and commonly applied in health research. A major advantage of this categorization, compared to other diagnostic categories, is that it groups diseases into clinically meaningful categories.

2.2 Episode-based Approach

Health care typically involves a variety of treatments (e.g., office visits, prescription drugs, lab tests) directed at a health condition over a period of time. Therefore, to provide a meaningful unit of analysis for analyzing the treatment of a condition, all of these services must be analyzed together. This is the basic concept underlying a health care episode. An episode may be defined as "...all the spending associated with a given bout of an illness, chronic condition, or well-care procedure" (Keeler et al. (1982)). Again, this is a natural unit of analysis, since it groups services related to the treatment of a particular disease, regardless of location or type of service or the specific diagnosis listed on a claim. Conceptually the episode classification is straight-forward, but in practice, a number of issues arise. In contrast to the encounter-based approach, the software is able to use individual history and comorbidities to assign diagnosis and severity levels. However, the episode-based approach still faces challenges when trying to assign services to episodes when there are multiple comorbidities. Another issue is how to identify the start and end of an episode. While chronic diseases are often analyzed over a fixed time period of a year, the determinants of start and stop times for other conditions are less clear.

This paper applies the two most widely-used commercial episode groupers to define disease episodes: the Medical Episode Grouper (MEG) by Truven Health Analytics and the Symmetry Episode Treatment Grouper (ETG) by Optum. These software programs have many similarities. Both apply algorithms that examine claim lines for each individual chronologically, and each claim line is assigned to a unique episode of care. The key information used to assign claim lines to disease episodes is the ICD-9 diagnosis on the claim. The method for assigning start and stop times for episodes is also similar. Certain types of claim line records are determined to be "anchor" records that can initiate an episode. For example, visits to physicians are often viewed as anchor records, since physicians are viewed as qualified to assign a diagnosis to a patient. In contrast, drug claims are not used as anchor records since

they do not contain a diagnosis and the same drug may be used to treat multiple illnesses. To end an episode, a certain amount of time without an associated claim record must pass, referred to as a "clean period". Although the default settings for defining anchor records and clean periods differ, both algorithms have the ability to customize these settings. For instance, researchers are able to customize which observations are considered "anchor" records and they are also able to set the number of days that are needed for a "clean period". Both groupers have around 500 disease categories, with ETG having 456 and MEG having 525. Both groupers provide additional disaggregation of the disease groups to account for the severity of the diseases, with up to four severity categories for a disease. In addition, both groupers account for associated comorbidities and complications when assigning a severity level. Neither of the grouper algorithms use procedure codes to classify diseases or severity levels.[5]

Many of the basic ideas underlying the groupers are similar, but the details and logic of each algorithm are distinct, leading to differences in the output. For example, in the case where there are two potential disease categories in which to place expenditures from a claim line, in some instances the ETG grouper will use procedure codes to determine the more appropriate category, while the MEG grouper will not. Although ETG and MEG have roughly 500 disease categories, the disease categories are distinct and there is no clear mapping across categories. Another difference in these algorithms is related to disease severity assignment. The ETG grouper will use the demographic information of the individual to classify severity, such as the individual's age, but the MEG grouper does not. In addition, the basic concept underlying the severity adjustment is different for each grouper. For the MEG, severity is thought of as the staging of the disease, capturing the natural progression of a disease toward increasing complexity: a disease stage of 1 signifies no complications, while a disease stage of 4 is death. In contrast, the ETG does not have a staging concept. Instead the severity levels are determined based on the distribution of illness severity in the population for each disease category.

This discussion traces out some general similarities and differences across these algorithms, but other researchers provide a more detailed examination. In particular, a comparison of how these algorithms allocate spending to different diseases has been explored using the Medicare population (MaCurdy et al. (2008)) and the commercially-insured population (Rosen et al. (2012)). As stated previously, our paper adds to these studies by looking at the different implications of these algorithms for measuring disease-price inflation.

[5] Although the ETG severity levels do not depend on procedures, there are numerous ETG subcategories that are determined by procedures. This allows researchers to examine certain disease episodes where the patients were treated similarly (e.g., ischemic heart disease with angioplasty). We do not study these subcategories in our analysis.

2.3 Person-based Approach

As an alternative to the approaches above, the person-based approach regresses total expenditures from an individual on indicator variables for whether the person has a given disease in a given time period. The indicator on each disease captures the marginal effect of each disease on expenditures. The regression coefficients can then be used to allocate expenditures across diseases. A key advantage of this approach is that it is less reliant on the diagnosis of a particular claim, but instead, relies on the statistical relationship between expenditures and disease indicators. This is particularly important for comorbidities, where certain diseases, such as diabetes, may affect the severity and treatment of other diseases, which may complicate the assignment of expenditures. The person-based approach also does a nice job of allocating expenditures for those services that do not have a listed diagnosis, as is common with prescription drug claims and lab tests. One challenge for the person-based approach is that it is based on an empirical model, so associated empirical issues such as bias or skewed data may affect the estimates. For instance, the presence of certain early stage or low severity diseases may indicate healthy patients that are actively treating their conditions, which may be correlated with better health and lower overall expenditures.

Researchers must consider a multitude of factors when applying a person-based approach. First, one must choose the disease categories to be included in the regression. For instance, one could use any of the disease categorizations discussed above, such as, ICD-9, CCS, MEG or ETG. Related to this point, researchers must determine if disease interactions should be included to account for more complicated comorbidities, such as an interaction between diabetes and heart disease. Second, the choice of the functional form of the regression may impact expenditure allocation across diseases. For instance, a linear regression may not appropriately capture the skewed and nonlinear relationship between diseases and expenditures. When applying nonlinear models, researchers must be careful to appropriately allocate expenditures across diseases, so that they properly add up to the original total, as demonstrated by Trogdon et al. (2008). A third issue is how to treat the intercept term in the regression. In this paper we explore a few possibilities: the intercept could be viewed as unallocated expenditures that are ignored, it could be treated as a "maintenance" disease category, or researchers could force all expenditures to be allocated across observable diseases.

2.4 Discussion

It is not clear which of the above approaches is best. However, there are certain scenarios where one approach may be preferred. For instance, in cases where diagnosis codes are often missing, the person-based approach may perform well, since the method can allocate expenditures across observable diseases. In cases where one would like to examine the underlying prices of services associated with a disease (e.g., Aizcorbe and Nestoriak (2011) and Dunn et al. (2014)), then it will be important to assign each claim line to an episode, so that prices of the associated services may be identified. In this case, the person-based approach will not work, and an episode-based or encounter-based method may be preferred. While there are a number of theoretical trade-offs for the different approaches, how much the selected methodology matters in practice is an empirical question. Before jumping to the data and analysis, we first discuss the basic framework for measuring growth in disease expenditures, disease episodes, and disease prices.

3 Decomposition: Expenditure Per Episode and Treated Prevalence

To begin, we start a measure of expenditure per capita for disease d for time period t, $C^*_{d,t}$ which is simply total expenditures for disease d in period t divided by the total commercially-insured population in period t. To simplify the analysis in this paper, we will assume that the demographics of the population is fixed (see Dunn et al. (2013)), so that the changing age of the population does not affect expenditure growth. To create a measure of medical-care expenditure growth, we form the following demographically-adjusted expenditure-per-capita index ($DECI$):

$$DECI_{d,t} = \frac{C^*_{d,t}}{C^*_{d,0}} \tag{1}$$

Next, we divide demographically-fixed expenditure per capita, $C^*_{d,t}$, into two components. One component is the treated prevalence disease index, $PREV_{d,t}$, which we define as growth in the prevalence of treated disease d, $prev_{d,t}$:

$$PREV_{d,t} = \frac{prev_{d,t}}{prev_{d,0}} \tag{2}$$

where $prev_{d,t}$ is simply the number of episodes treated in the population divided by the commercially-insured population, holding fixed the demographic distribution. Note that $prev_{d,t}$ includes only those that are aware of their condition and seek some medical attention and excludes those individuals that do not seek treatment.[6]

[6] Those individuals that do not seek medical attention or may even be unaware of their condition would be counted when measuring

The second component of $C^*_{d,t}$ is the expenditure per episode d, $c_{d,t}$. The value $c_{d,t}$ may be calculated by dividing total expenditures of disease d by the number of episodes of disease d in period t. It follows that the "medical-care expenditure index," the MCE index, is a measure of the medical-care expenditures for the treatment of a certain disease episode, and is defined as the dollar amount of medical care used for treatment.[7] Denoting $c_{d,0}$ as the average expenditure per episode in the base period, $t = 0$, the MCE index for disease d is the ratio of the two measures:

$$MCE_{d,t} = \frac{c_{d,t}}{c_{d,0}} \tag{3}$$

Since this index controls for the health of the individual, it may be viewed as measuring the cost of treatment. Thus, if the $MCE_{d,t}$ is larger than one, it signifies that the expenditure for treating disease d is larger than the base period, and if the index is less than one, it signifies that the expenditure is less than the base.

Using these equations it follows that $C^*_{d,t} = c_{d,t} \cdot \ prev_{d,t}$. From this we can see that the $DECI_{d,t}$ may be decomposed into its two components, which include the episode-based index, $MCE_{d,t}$ and the treated prevalence disease index, $PREV_{d,t}$. The additive decomposition is

$$DECI_{d,t} = MCE_{d,t} + PREV_{d,t} + \frac{(prev_{d,t} - prev_{d,0})(c_{d,t} - c_{d,0})}{prev_{d,0}c_{d,0}} - 1. \tag{4}$$

[8]

This equation makes it clear that the $DECI$ will rise if there is either an increase in the $PREV_{d,t}$ or an increase in $MCE_{d,t}$. These two components of expenditure capture distinct elements of cost growth. Changes in the treated prevalence of a condition may capture the changing health of the population, such as the growth in diabetes due to obesity. It may also reflect a growing awareness of a condition, such as the increase in awareness and diagnosis of high cholesterol. The second component of care may be viewed as the price for treating the disease, which includes

the population's prevalence, which makes the population's prevalence different from the *treated* prevalence.

[7] For example, for an individual with a broken foot, the episode of treatment will be defined by the dollar of medical services used to treat that condition from the first visit to a provider until the foot is healed. For medical conditions that are chronic, we interpret an episode as expenditures for services used to treat the chronic conditions over a one-year period.

[8] The multiplictive decomposition is:

$$\begin{aligned} DECI_{d,t} &= MCE_{d,t} \cdot PREV_{d,t} \\ \log(DECI_{d,t}) &= \log(MCE_{d,t}) + \log(PREV_{d,t}) \end{aligned}$$

the prices of those services and the mix of those services provided. Assuming that the quality of the underlying treatment mix remains constant, this treatment price may be used as a deflator to determine the change in output in the health sector.

The indexes presented here are directly related to demographically-adjusted total medical-care expenditures per capita. To see this, we can create aggregate disease-specific indexes from the measure, $DECI_{d,t}$. When $DECI_{d,t}$ is weighted by the national expenditure share for each disease in the base period, it becomes a measure of medical-care expenditures per capita relative to the base period's medical-care expenditures per capita:

$$\begin{aligned} DECI_t &= \sum_D DECI_{d,t} \cdot (\text{Expenditure Share}_0) \\ &= \sum_D \frac{C^*_{d,t}}{C^*_{d,0}} \cdot \left(\frac{C^*_{d,0}}{\sum_D C^*_{d,0}} \right) = \frac{\sum_D C^*_{d,t}}{\sum_D C^*_{d,0}} \\ &= \frac{\text{Medical-Care Expenditures Per Person}_t}{\text{Medical-Care Expenditures Per Person}_0}. \end{aligned}$$

3.1 Applying the Different Approaches

To apply the above decomposition, expenditures must be assigned to a particular disease. In the case of using an encounter-based approach or an episode-based approach, the calculation is straightforward. Specifically, each claim line in the data is associated with an individual i and will be assigned to disease episode d. Let individual i's expenditures for disease episode d be $c_{d,i}$. The total expenditures for an individual, c_i, are then the summation over disease episode expenditures and unallocated expenditures, $c_i = \sum_{d \in D_i} c_{d,i} +$ unallocated expenditures$_i$, where D_i is the set of all disease episodes for individual i and the number of treated episodes for the individual is $\sum_{d \in D_i} 1$.

The application of the person-based approach has additional steps, since the regression is needed to uncover the disease expenditure allocation for each individual. Specifically, it is assumed that the researcher observes total expenditures per individual, c_i, and they observe the set of diseases for each individual, D_i. However, the goal of the regression analysis is to uncover the individual disease episode expenditures, $c_{d,i}$, through the regression estimation. The person-based approach takes two steps. The first step is to specify the regression model that will be run separately on each year of the data. For example, for each year t we run an OLS regression on $\ln(c_{i,t}) = \beta_{0,t} + \sum_{d \in D_{i,t}} \beta_{d,t} \mathrm{I}_{d,i,t} + v_{i,t}$, where $\mathrm{I}_{d,i,t}$ is an indicator that is 1 if individual i has disease d and zero otherwise. In the second step, the parameter estimates from the regression are used to determine the expected total expenditure for each disease. To do this, the expenditure share for individual i's disease d is computed as $\widehat{s}_{d,i,t} = \frac{\exp(\widehat{\beta}_{d,t})}{\exp(\sum_{d \in D_{i,t}} \widehat{\beta}_{d,t} I_{d,i,t})}$. The total estimated

expenditure that is allocated to diseases is computed as: $\widehat{c}_{i,t} = \exp(\widehat{\beta}_{0,t} + \sum_{d \in D_{i,t}} \widehat{\beta}_d \mathrm{I}_{d,i,t} + \widehat{v}_{i,t}) - \exp(\widehat{\beta}_{0,t} + \widehat{v}_{i,t})$. The estimated allocation of disease episode d for person i is then $\widehat{c}_{d,i,t} = \widehat{s}_{d,i,t} \cdot \widehat{c}_{i,t}$. With the estimate of $\widehat{c}_{d,i,t}$, all the necessary information is available to compute the various indexes.

It should be noted that there are a number of alternative ways to estimate the regression model. For instance, one may estimate a linear OLS regression model or, alternatively, a GLM model to account for the skewed distributional properties of the data. In addition, there are different approaches for using the regression output to allocate expenditures. For instance, the intercept term, $\exp(\widehat{\beta}_0 + \widehat{v}_i)$, could either be thought of as unallocated expenditures or it could be considered as a separate disease category. For instance, one may think of the intercept as some type of "maintenance" cost for unspecified health issues. Alternatively, one could force the allocation of all individual expenditures across diseases by calculating the expenditures for disease episode d for person i as $\widehat{c}_{d,i} = \widehat{s}_{d,i} \cdot c_i$. This approach has the appeal of allocating nearly all expenditures to a well-defined episode category. In our analysis section, we will explore how these various assumptions potentially affect disease-price inflation.

4 Data

We use retrospective claims data for a sample of commercially insured enrollees from the MarketScan® Research Database from Truven Health. The specific claims data used is the Commercial Claims and Encounters Database which contains data from employer and health plan sources containing medical and drug data for several million commercially insured individuals, including employees, their spouses, and dependents. Each observation in the data corresponds to a line item in an "explanation of benefits" form in a medical claim. Each claim can consist of many records, and each encounter can consist of many claims.

We use a sample of enrollees that are not in capitated plans from the MarketScan database for the years 2003 to 2007. We also limit our sample to enrollees with drug benefits because drug purchases will not be observed for individuals without drug coverage. The MarketScan database tracks claims from all providers using a nationwide convenience sample of enrollees. To ensure that we observe all of an individual's expenditures for a year, we limit the sample to those enrollees that have a full year of continuous enrollment. Each enrollee has a unique identifier and include age, sex, and region information that may be used when calculating patient weights. All claims have been paid and adjudicated.

The claims data were processed using the Symmetry Episode Treatment Group (ETG) from Optum and the

Medical Episode Grouper (MEG) from Truven Health. Both groupers assign each claim to a particular episode group. Thus each disease category d represents a type of disease (e.g., hypertension). In cases where severity adjustment is applied, the disease category d will represent a type of disease as well as the severity (or staging) of the disease. In this case, an episode of severity three hypertension, "hypertension 3", is a distinct disease with a higher severity relative to the lower severity category "hypertension 1".

For both the ETG Symmetry grouper and the MEG grouper, the algorithms are applied to one calendar year of data at a time. Although this limits the amount of information used for each person (since we often observe multiple years), it also avoids potential biases that may occur if the grouper is not applied symmetrically across all years, which will be discussed in additional detail later. In addition to applying groupers to the data, we also applied the mapping of the ICD-9 disease codes to the Clinical Classification Software (CCS) codes,which is another disease classification system examined in our analysis. Demographic weights are applied to adjust for differences in age, sex, and region.[9]

4.1 Descriptive Statistics

Each of the approaches to allocating expenditures to diseases ultimately depends on assigning diseases to the claims of an individual. Even the person-based approach relies on the diagnosis listed on the claims. Therefore, before stepping into the analysis of how the different methodologies affect disease-price inflation, it is useful to understand some basic features of the encounter and episode approaches for assigning claim lines to disease categories. First, it is important to note that the three disease classification systems considered here, ETG, CCS and MEG, differ in their share of expenditures allocated to diseases. For comparison in 2007, the ETG grouper allocates 87 percent of expenditures; the MEG grouper allocated 83 percent of expenditures; and the CCS encounter-based approach allocated 84 percent of expenditures. Those claims that are not assigned to a disease episode are considered ungrouped or unallocated. A primary reason that the MEG and ETG groupers do not allocate claims is that there is not an associated anchor record (e.g., a visit to a physician where a diagnosis is observed). For the CCS categorization, prescription drugs and other claims that do not have an associated diagnosis code are not allocated to a disease.

[9] Specifically, enrollees in each year are assigned weights so the weighted population has an age and sex distribution that is identical to that of the U.S. commercially insured population in 2007. Information on the population to construct population weights is obtained from the Current Population Survey from the U.S. Census Bureau.

The three different approaches assign each claim line to distinct diseases. To see this, Table 1 shows the top ten ETG diseases based on expenditures for 2007. The first column shows the ETG category and the second column shows the total expenditures allocated to that ETG category. For each ETG category listed, the third column shows four MEG categories that correspond to those ETG expenditures, ranked based on the MEG expenditure share. For example, the first ETG category listed, ischemic heart disease: the MEG grouper assigns 53.6 percent of those expenditures to the MEG category "Angina Pectoris, Chronic Maintenance", 19.8 percent are assigned to "Acute Myocardial Infraction", 9.2 percent are ungrouped, and 4.0 percent are assigned to "Arrhythmias". There are a few general points worth noting. First, it is clear that the MEG and ETG categories are distinct. Consequently, many of the ETG disease categories are spread across multiple, although often related, MEG disease categories. As can be seen by the first example, the MEG categories "Angina Pectoris, Chronic Maintenance", "Arrhythmias", and "Acute Myocardial Infraction" are closely associated with ischemic heart disease from a clinical perspective. Second, there are many instances where the ETG grouper assigns a disease, but the MEG does not.

Table 1. Top Ten ETG Disease Categories Mapped to MEG Classification

ETG	Total Expenditures (millions)	MEG	% Exp. MEG on ETG	Cumulative % Exp. of MEG on ETG
Ischemic heart disease	$24,954	Angina Pectoris, Chronic Maintenance	53.6%	53.6%
Ischemic heart disease		Acute Myocardial Infarction	19.8%	73.4%
Ischemic heart disease		Ungroupable Medical Claims	9.2%	82.6%
Ischemic heart disease		Arrhythmias	4.0%	86.6%
Pregnancy, with delivery	$23,557	Delivery, Vaginal	88.3%	88.3%
Pregnancy, with delivery		Ungroupable Medical Claims	7.0%	95.3%
Pregnancy, with delivery		Ante- and Postpartum Complications	1.5%	96.7%
Pregnancy, with delivery		Delivery, Cesarean Section	1.0%	97.8%
Joint degeneration, localized - back	$19,846	Osteoarthritis, Lumbar Spine	31.2%	31.2%
Joint degeneration, localized - back		Intervertebral Disc Disorders: Lumbar and Lumbosacral	24.4%	55.6%
Joint degeneration, localized - back		Other Spinal and Back Disorders: Low Back	16.4%	72.0%
Joint degeneration, localized - back		Ungroupable Medical Claims	15.5%	87.5%
Diabetes	$19,189	Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance	44.3%	44.3%
Diabetes		Ungroupable Medical Claims	23.3%	67.5%
Diabetes		Diabetes Mellitus Type 1 Maintenance	18.2%	85.7%
Diabetes		Diabetes Mellitus with Complications	2.7%	88.4%
Hypertension	$16,574	Essential Hypertension, Chronic Maintenance	60.5%	60.5%
Hypertension		Ungroupable Medical Claims	16.3%	76.8%
Hypertension		Other Respiratory Symptoms	3.3%	80.1%
Hypertension		Angina Pectoris, Chronic Maintenance	2.5%	82.6%
Routine exam	$14,765	Encounter for Preventive Health Services	84.6%	84.6%
Routine exam		Ungroupable Medical Claims	8.4%	93.0%
Routine exam		Factors Influencing Health Status	3.8%	96.8%
Routine exam		Other Cardiovascular Symptoms	0.2%	97.0%
Malignant neoplasm of breast	$14,168	Neoplasm, Malignant: Breast, Female	78.3%	78.3%
Malignant neoplasm of breast		Ungroupable Medical Claims	13.8%	92.0%
Malignant neoplasm of breast		Neoplasm, Benign: Breast	1.5%	93.5%
Malignant neoplasm of breast		Factors Influencing Health Status	1.4%	95.0%
Mood disorder, depressed	$10,327	Depression	64.6%	64.6%
Mood disorder, depressed		Ungroupable Medical Claims	12.8%	77.4%
Mood disorder, depressed		Generalized Anxiety Disorder	4.3%	81.8%
Mood disorder, depressed		Bipolar Disorder - Major Depressive Episode	2.8%	84.6%
Joint degeneration, localized - neck	$9,051	Osteoarthritis, Cervical Spine	27.7%	27.7%
Joint degeneration, localized - neck		Intervertebral Disc Disorders: Cervical	26.9%	54.5%
Joint degeneration, localized - neck		Ungroupable Medical Claims	16.9%	71.4%
Joint degeneration, localized - neck		Other Spinal and Back Disorders: Cervical	14.4%	85.8%
Non-malignant neoplasm of female genital tract	$8,898	Neoplasm, Benign: Uterus (Leiomyomas)	27.4%	27.4%
Non-malignant neoplasm of female genital tract		Dysfunctional Uterine Bleeding	15.0%	42.4%
Non-malignant neoplasm of female genital tract		Ungroupable Medical Claims	13.9%	56.3%
Non-malignant neoplasm of female genital tract		Other Disorders of Female Genital System	13.5%	69.8%

notes: Table 1 shows the top 10 ETG disease categories based on expenditure share for 2007. Four of the corresponding MEG categories are shown in order of highest allocation to lowest allocation.

The patterns observed in Table 1 are also observed when looking at these expenditure mappings in the other direction, that is, when looking at the top MEG categories and the associated ETG assignment (see Table A1.1 of the Appendix). Similar patterns also emerge when comparing ETG categories to the CCS classification (see Table A1.2 of the Appendix). The one primary difference is that the CCS categorization does a particularly poor job of assigning expenditures for those diseases that use a significant amount of prescription drugs for treatment, since diagnosis codes used by the encounter-based approach are not available for prescription drugs. For instance, for the ETG category "Diabetes", the CCS classification is not able to classify 48 percent of the associated expenditures.

Clearly these three methods of assigning expenditures are distinct, which matches the findings of Rosen et al. (2012). Next, we look at whether these differences have implications for disease-price inflation.

5 Results

In Table 2 we compare aggregate trends for nine different approaches for decomposing medical care expenditure growth. The table lists the name of the method in the first column, followed by the aggregate $DECI$, $PREV$, and MCE. The first six apply a grouper approach, the seventh applies an encounter-based approach, and the last two rows apply a person-based approach. Before going through each of the different approaches, we first highlight the differences in the $DECI$ across these different approaches. Recall that the aggregate $DECI$ is essentially a demographically-adjusted expenditure per capita index, where the expenditures included in the calculation are the expenditures that we are able to group or assign to a specific disease. Therefore, the only difference in the index across these different approaches is the share of expenditures allocated over time. The table shows that the $DECI$ is similar across nearly all of the approaches, ranging from 1.22 to 1.25. One of the notable endpoints of this range is the encounter-based approach, method 7, which has a $DECI$ that falls to one extreme, 1.224. It is not surprising that the CCS encounter estimate is different than the others, since it excludes drug claims that do not have diagnosis information.

The primary difference across these different methodologies is the decomposition of the $DECI$ between $PREV$ and MCE. Method 1 applies the ETG grouper with severity adjustment, which produces relatively slow MCE growth of 1.14, accounting for a little over half of expenditure growth. Method 2 applies the ETG grouper without severity adjustment and shows a slightly faster MCE growth rate. A likely reason for this difference is that there has been growth in treated prevalence for some higher severity diseases. Therefore, the non-severity adjusted MCE will reflect the mix of higher severity diseases and show faster price growth. Method 3 and 4 apply the MEG grouper, severity adjusted and not severity adjusted, respectively. The MEG MCE indexes grow slightly faster than the ETG indexes, and the MEG severity adjustments have little measurable effect on the aggregate indexes.

Methods 1 through 4 are all based on the concept of an episode, as defined by the MEG and ETG grouper, where a person may have multiple episodes in a single year. For some applications, it may be more appropriate to consider disease expenditures per person in a year or quarter, rather than expenditures per episode. For instance, Aizcorbe and Nestoriak (2011) apply disease expenditures per person in a quarter rather than expenditures per episode, while Dunn et al. (2012) look at expenditure per person on an annual basis.[10] To investigate if "annualizing" episodes has

[10] The annualized episode is actually more consistent with the regression and encounter approaches as those also price diseases on an annual basis.

an effect on the estimates, method 5 repeats the analysis of method 2, but redefines an episode to correspond to a calendar year.[11] Despite this difference, the results look nearly identical to the results of method 2.

Table 2. Growth Decomposition for 2003 to 2007 - Grouper-, Encounter- and Person-based Approaches

Method	DECI	PREV	MCE
Grouper			
1. ETG Severity Adjusted (Baseline)	1.250	1.103	1.139
2. ETG Not Severity Adjusted	1.250	1.098	1.147
3. MEG Severity Adjusted	1.240	1.074	1.163
4. MEG Not Severity Adjusted	1.240	1.071	1.164
5. ETG Annual Episodes (Not Severity Adjusted)	1.250	1.098	1.146
6. ETG - Episodes by MPC Class	1.250	1.077	1.165
Encounter			
7. Primary Diagnosis - CCS Disease Categories	1.224	1.028	1.178
Person - Regression Analysis			
8. ETG Severity-Adjusted	1.233	1.091	1.131
9. CCS Disease Category	1.240	1.072	1.150

notes: The regression-based approaches of 8 and 9 apply log linear regressions. The expenditures allocated to the intercept are considered unallocated and are excluded from the analysis.

One concern with methods 1 through 5 is that they may be highly sensitive to doctor diagnostic coding practices.[12] For example, an individual with heart disease may have numerous related cardiovascular illnesses and complications. In this case, it is possible for there to be some discretion by the physician deciding how many related conditions to record. Trends in coding practices could potentially affect the analysis, leading to changes in the MCE that do not reflect shifts in actual treatment costs. To investigate the sensitivity of the analysis to this potential issue, we group episodes into more broadly defined condition categories to limit the effects of a growing number of diagnoses. In the heart disease example, applying the broader categorization would lump heart disease and other cardiovascular conditions into the same "cardiovascular" episode, so the disease price will not be affected by an increase in listed cardiovascular conditions. To apply the more broadly defined disease categories, the ETG categories are grouped into 21 broadly defined Major Practice Categories (MPC), and an episode is counted if an individual is treated for one of the MPC categories for that year. The results are reported in method 6. We find that relative to methods 1 and 2, the MCE growth from method 6 is slightly faster. This suggests that some of the growth in treated prevalence

[11] For example, if a person had two episodes of the same disease within a year using method 1, then applying method 5 would count the two episodes as a single episode.

[12] Indeed, Song et al. (2010) provides evidence that there are significant differences in coding practices across geographic markets for the Medicare population.

is due to an increase in observing multiple cases within one MPC category. However, the within-category growth of treated prevalence appears to be only a small percentage of the total growth. In fact, the growth rate using this approach is quite similar to that found using the MEG grouper. Of course, the more broadly defined categories may also be problematic. Specifically, more broadly defined disease categories are likely to include very heterogenous conditions (e.g., hypertension and heart disease), which could cause serious measurement problems. The issue of the MCE being sensitive to diagnostic practices is analyzed further in the following subsection using an alternative methodology.

Method 7 presents the encounter-based approach, which is quite different from the other approaches, since it does not classify drug claims. That is, drug expenditures are excluded from method 7, but they are included in all the other methodologies. Consequently, each component of expenditure growth is distinct from methods 1 through 6. A major reason for this stark contrast is that much of the growth in treated prevalence for methods 1 through 6 is for diseases that are typically treated with prescription drugs, such as hyperlipidimia (i.e., high cholesterol), hypertension (i.e., high blood pressure) and diabetes.

Each of the methods 1 through 7 rely on a mapping of each claim line to a particular disease category. In contrast, the last two methods in Table 2 rely on the person-based approach, which uses regression analysis to allocate disease expenditures. Method 8 uses severity adjusted ETG disease classification in the regression model. Although the method is quite distinct from method 1, the results are fairly similar. One distinction is that the $DECI$ is lower, due to a change in the share of expenditures allocated over time, but the MCE estimate does not change. Finally, method 9 also applies the person-based approach, but uses the CCS categories instead of the ETG categories. Unlike the encounter-based approach of method 7, the regression using the CCS condition categories is able to allocate drug expenditures. Once these expenditures are allocated based on the regression estimates, the MCE growth using CCS categories appears similar to the other approaches.

For some researchers selecting among different approaches, it is worth noting that method 9 is appealing for three reasons. First, the method is based on the CCS categories, which is a nonproprietary categorization system that is commonly used by health researchers. Second, unlike method 7, the person-based approach exploits estimates from the regression that are able to allocate the drug expenditures. Finally, the estimates appear reasonable, falling in the middle of the range of the other estimates reported in Table 2. However, as with all of the methods, there are trade-offs. For instance, method 9 does not account for the severity of a patient's illness. In addition, method

9 is a person-based approach that does not allocate particular services to episodes, which is important for many applications.

The analysis in Table 2 shows some differences in disease-price inflation rates that demonstrate that the MCE is impacted by disease allocation methodologies. However, given the vast differences in the approaches, the similarities in the finding are striking. In particular, applying the methodologies from Table 2 (excluding method 7 that removes drug claims) the table shows MCE growth rates ranging from 1.128 (CAGR 3.1 percent) to 1.165 (CAGR 3.9 percent), which implies a difference in CAGR of about 0.8 percent across methodologies.

5.1 Alternative Person-Based Estimates

The person-based approach is fundamentally different from the encounter-based and episode-based methodologies because it relies on an empirical model specified by the researcher. This introduces additional flexibility in selecting among different regression models and allocating expenditures. This subsection explores additional person-based disease price estimates, which are reported in Table 3. As a baseline, the first row of Table 3 repeats the estimates from method 8 in Table 2. An underlying assumption in method 1 is that the expenditures that are allocated to the intercept of the regression model are considered unallocated and are dropped from the estimates. Alternatively, one could assume that all expenditures should be allocated to the observed diseases. Method 2 is identical to method 1, but all expenditures are allocated to the listed ETG diseases for each person.[13] One advantage of this approach is that it reduces ungrouped expenditures to less than 1 percent of total expenditures. Method 2 shows an aggregate MCE growth rate that is only slightly lower than method 1. Alternatively, rather than force the expenditures allocated to the intercept across the observable diseases, one could treat the intercept as a distinct disease category, which is the approach taken in method 3. Again, the results change only slightly from method 1 estimates.

Another assumption of method 1 is that it applies the ETG severity adjustment. Method 4 applies the same methodology as method 1, but does not severity adjust. Again, this approach shows results quite similar to Method 1 with only slightly faster MCE growth. This difference between severity adjusting and not severity adjusting parallels the results using the ETG episode-based approaches reported in Table 2.

All of the previous estimates only incorporate the diagnosis of the patient and include no additional information. Method 5 attempts to control for the age and sex of each patient by constructing unique disease prices for four

[13] If a person has expenditures with no associated ETG, then those expenditures would be unallocated.

categories of individuals: males above 50, males below 50, females below 50, and females above 50. After constructing separate indexes for each age, sex and disease category, the estimates are aggregated based on the expenditure share in the base period for each age-sex-disease combination.[14] Accounting for these major age and sex differences has only minor effects on the aggregate estimates.

Table 3. Growth Decomposition for 2003 to 2007 - Person-based Estimates

Person-based Method	DECI	PREV	MCE
1. ETG Severity-Adjusted (same as row 8. of Table 1)	1.233	1.091	1.131
2. Same as (1), with Expenditures Forced to Observable Diseases	1.225	1.091	1.123
3. Same as (1) , with Intercept Considered Separate Disease	1.223	1.077	1.138
4. Same as (1), with No Severity Adjustment	1.240	1.088	1.142
5. Repeat (4) using Gender and Age Interactions	1.243	1.087	1.145
6. Repeat (4) using Comorbidity Interactions	1.239	1.088	1.142
7. Repeat (4) using Only Frequently Appearing Diseases	1.246	1.098	1.139

One advantage of the person-based approach is that it allows for additional flexibility in measuring disease prices for more complex patients with comorbidities. To customize our empirical model to account for comorbidities, additional interaction terms are included in the regression models, which allows those with a single medical condition to have an allocation distinct from those with multiple conditions. For example, a person with both diabetes and heart disease may have a distinct expenditure growth pattern compared to a person with only heart disease or only diabetes. In method 6 we incorporate many common comorbidity interactions, such as diabetes and heart disease, as an approach for accounting for these comorbidities. Despite the observation that a vast majority of expenditures are made by those with multiple conditions, these estimates show that accounting for comorbidities has no effect on the aggregate disease-price growth rates in our sample.

Method 7 revisits the topic of checking whether changes in diagnostic practices may impact MCE measurement. For method 7 only those diseases that have at least three associated encounters are classified as diseases. For instance, if a person has just one or two visits to a doctor for the treatment of hypertension, but no other observations related to hypertension, then hypertension will not be included as a disease in the regression. This should help reduce the impact of coding practices or potential coding errors on MCE measurement. Using this alternative methodology, we find estimates that are closely in line with the others reported in Tables 2 and 3.

[14] Because we are using a commercially-insured population the age range is from 0 to 64.

5.2 Disease Category Comparisons

While the aggregate disease-price growth patterns are similar across disease-allocation strategies, it is not certain that these patterns are also similar for specific disease categories. To explore these differences, Table 4 presents the disease-price growth estimates at the disease-category level for three different methods. Each of the methods compared in Table 4 are based on ETGs, which may be aggregated into broader Major Practice Categories (MPCs). The first set of estimates applies the episode-based approach (Table 2, method 1). The method 1 estimates show that trends for each disease category may be quite different, and may not follow the general trend. For example, expenditures for preventative services rise much faster than the aggregate, while cardiology rises slower. There are also large differences in the disease prices (e.g., the MCE for cardiology rising much slower than most other categories). The second set of results is from the person-based approach using severity adjusted ETGs in the regression (Table 2, method 8). Generally, the results from the first and second set of estimates are positively correlated. Specifically, the correlation for the $DECI$ is 0.579, the correlation for the $PREV$ is 0.903, and the correlation for the MCE is 0.746, but despite the positive correlation, there are many clear differences. For instance, the prevalence growth for the endocrinology condition category using the person-based method is 10 percentage points lower than the estimates using the episode-based approach. It is also worth noting that these correlations are much higher for the higher expenditure categories. The correlation across indexes are all above 88 percent if one looks at only those categories that account for more than 3 percent of spending. The third column of results applies the episode-based approach, but uses the broad MPC categories (Table 3, method 6). Again, the results are positively correlated with the other two approaches, but the results are clearly different. In particular, the MCE price growth tends to be faster than the other two methods, following the pattern of the aggregate results. One interesting exception is the MCE growth rate for Cardiology, which actually grows slower than the other two methods.

Despite these differences in the methods, some general patterns emerge at the disease category level. Specifically, for cardiology conditions, we see price growth and prevalence growth is quite slow. In contrast, for preventative services, we see expenditure growth increasing rapidly, due to both higher treated prevalence and higher prices. Treated prevalence growth rate for endocrinology conditions appear to be much faster than the overall trend, likely due to increases in the treated prevalence for diseases like diabetes and high cholesterol.

Table 4. ETG-based Decompositions by Major Practice Category

		1			2			3		
		Episode-Decomp. Table 2. Method(1)			Person-based Decomp. Table 2. Method (8)			Episode-Decomp. Table 2. Method (6)		
Description	Expenditure Share	DECI	PREV	MCE	DECI	PREV	MCE	DECI	PREV	MCE
Orthopedics & rheumatology	14.0%	1.300	1.119	1.165	1.240	1.079	1.151	1.280	1.054	1.215
Cardiology	12.0%	1.108	1.043	1.059	1.113	1.042	1.069	1.101	1.074	1.025
Endocrinology	8.9%	1.343	1.273	1.074	1.280	1.177	1.097	1.329	1.155	1.150
Gastroenterology	8.4%	1.288	1.111	1.169	1.277	1.088	1.168	1.281	1.067	1.200
Preventive & administrative	6.4%	1.625	1.290	1.261	1.685	1.284	1.298	1.611	1.256	1.283
Otolaryngology	5.7%	1.140	1.027	1.111	1.201	1.076	1.120	1.156	1.002	1.154
Gynecology	5.5%	1.215	1.006	1.203	1.160	1.022	1.132	1.223	1.007	1.214
Dermatology	4.9%	1.276	1.084	1.178	1.253	1.067	1.168	1.270	1.047	1.213
Psychiatry	4.8%	1.261	1.130	1.115	1.248	1.128	1.100	1.263	1.134	1.114
Neurology	4.7%	1.299	1.097	1.187	1.248	1.076	1.167	1.283	1.045	1.228
Pulmonology	4.6%	1.162	1.012	1.158	1.090	0.994	1.119	1.158	0.936	1.237
Obstetrics	4.5%	1.259	1.076	1.171	1.243	1.072	1.161	1.262	1.043	1.210
Urology	3.1%	1.224	1.118	1.112	1.190	1.090	1.107	1.220	1.046	1.166
Isolated signs & symptoms	2.9%	1.115	1.002	1.112	1.368	1.168	1.171	1.334	1.168	1.142
Hematology	1.9%	1.278	1.112	1.149	1.296	1.089	1.185	1.277	1.071	1.192
Hepatology	1.7%	1.118	0.993	1.120	1.052	0.985	1.061	1.119	1.016	1.102
Ophthalmology	1.6%	1.189	1.127	1.054	1.184	1.128	1.061	1.183	1.094	1.082
Nephrology	1.0%	1.329	1.485	0.903	0.801	1.347	0.634	1.428	1.219	1.171
Neonatology	1.0%	1.317	1.140	1.169	1.210	1.127	1.082	1.312	1.043	1.257
Infectious diseases	1.0%	1.380	1.154	1.176	1.267	1.118	1.132	1.373	0.919	1.494
Late effects, envir. trauma & pois.	0.8%	1.273	0.957	1.339	1.085	0.942	1.153	1.259	0.960	1.311
Chemical dependency	0.7%	1.415	1.377	1.057	1.630	1.426	1.164	1.404	1.563	0.898
Total Expenditures (in Billions) 2007	$604									

notes: Expenditures used to calculate expenditure share are calculated from the person-based decomposition, Table 2, Method (8).

Table 5 also compares decompositions of growth rates at the disease level, but it includes non-ETG approaches. Specifically, it includes the severity-adjusted ETG results (Table 2, method 1) along with the severity-adjusted MEG results (Table 2, method 4) and another using person-based CCS results (Table 2, method 7). There is no correspondence among the MEG, CCS, and ETG categories, so we can not compare these approaches precisely at the disease level. Instead, we compare broad condition categories that appear to be related based on the names of the categories. It should be highlighted that these categorization systems are quite distinct, so comparing across these systems may be problematic. For instance, neoplasms is a distinct category for CCS classification, while for the ETG neoplasms fall under the associated practice category (e.g., lung cancer is categorized under pulmonology). The first column reports the name of the category and the second column reports the associated allocation methodology. The last three columns show the indexes. In some cases, the results look roughly similar, such as for cardiology-related conditions. However, there are many instances of larger differences. For instance, the MCE for the MEG category, "Endocrine and Metabolic" grows quite fast, with a value of 1.189, while the MCE for the seemingly related CCS category "Endocrine; nutritional; and metabolic" grows relatively slowly (1.043). For a full disease-category

decomposition of both the CCS and MEG results see Tables A5.1 and A5.2 of the appendix.

Table 5. Comparison ETG Decompositions with Non-ETG Methods

Description		DECI	PREV	MCE
Orthopedics & rheumatology	ETG	1.300	1.119	1.165
Musculoskeletal Connective Tissue	MEG	1.306	1.082	1.210
Diseases of the musculoskeletal system	CCS Person-Based	1.246	1.099	1.132
Cardiology	ETG	1.108	1.043	1.059
Cardiovascular	MEG	1.110	1.013	1.092
Diseases of the circulatory system	CCS Person-Based	1.098	1.035	1.062
Endocrinology	ETG	1.344	1.273	1.074
Endocrine and Metabolic	MEG	1.410	1.191	1.189
Endocrine; nutritional; and metabol	CCS Person-Based	1.233	1.185	1.043
Gastroenterology	ETG	1.288	1.111	1.169
Gastrointestinal	MEG	1.272	1.062	1.202
Diseases of the digestive system	CCS Person-Based	1.143	1.035	1.104

notes: The category names selected suggest some similarities in the types of diseases included across the different categories grouped in this table. However, both the underlying diseases and the aggregation of diseases are distinct across the different classification systems. For instance, neoplasms is a distinct category for CCS classification, while for ETG neoplasms fall under the associated practice category (e.g., lung cancer is categorized under pulmonology). The CCS decomposition is based on a person-based decomposition.

5.2.1 Some lessons for calculating disease-price inflation

1. *Different methods for grouping claims should be explored.* The estimates in this paper show several alternative approaches for allocating disease episodes. Several reasonable approaches lead to differences in disease-price inflation, although many of the estimates tend to fall in a close range. The importance of the magnitude of these differences will depend on the application. In any case, checking if alternative approaches lead to similar inflation patterns is useful to understand the robustness of the findings. For instance, it may be useful to see if patterns observed applying one methodology hold when an alterative approach is applied. For practical purposes, we also find that applying multiple approaches is useful for identifying coding errors or implementation problems, since estimates that fall far outside the range of other estimates may suggest a potential problem. For example, in Table 2, method 7 shows growth patterns that are distinct from the other approaches, but this is primarily the result of omitting drug expenditures. The selected approach will likely depend on the researchers objectives. For instance, some methods allocate nearly all expenditures to a disease (e.g., Table 3, method 2 or method 3), while other approaches do not (e.g., Table 2, method 1). On the other hand, researchers may be interested in applying a categorization system that is centered around episode grouping, while others may be more interested in using a categorization system, such as the CCS, that has been more broadly applied in the literature

2. *Claims information should be analyzed symmetrically across years.* The episode-based estimates above rely on

grouper software that is applied to the claims data one year at a time. Alternatively, one could also run the grouper on the entire history of claims. One advantage of this alternative approach is that the grouper software is able to allocate a greater share of claims, and also allocate those claims more precisely, since it learns more about individuals over time.[15] However, this can also lead to substantial biases when looking at inflation, since more information will be observed for individuals in later years than in earlier years. To demonstrate the effect of this bias, we conduct our analysis on a fixed sample of individuals - specifically, including those individuals that enter the data in 2003 and do not leave the sample. It should be noted that the selected subsample of 500,000 individuals may produce rapid expenditure growth figures. Expenditure estimates are biased upward for this sample because individuals in the beginning of the sample are healthier than those at the end of the sample, since those in the beginning of the sample are *all* more than four years away from dying.[16] The results of the analysis are shown in Table 6.

Table 6. ETG Symmetry Grouper - Fixed Enrollee Sample

Person-based Regression Method	% Not Grouped 2003	% Not Grouped 2007	DECI	PREV	MCE
1. Grouper Algorithm Applied Continuously Over Entire Sample	15.5%	10.6%	1.532	1.417	1.079
2. Grouper Algorithm Applied One Year at a Time	16.7%	15.2%	1.511	1.225	1.194

notes: The analysis is based on enrollees that are in the sample from 2003 to 2007. The grouper is applied two distinct ways: (1) continuously over the entire sample, starting in 2003; (2) one year at a time (i.e., 2003, 2004, 2005, etc.).

The first row shows results for the claims that are continuously grouped using the ETG Symmetry grouper, while the second row shows results for the same sample that is grouped one year at a time. The first two columns of Table 6 show the percentage of expenditures not grouped in 2003 and 2007 for each of these two methods. As expected, due to the additional historical information used in the continuously grouped analysis, the share of expenditures grouped in 2007 is much larger than the share grouped in 2003. In contrast, the share of grouped expenditures for the data that is grouped one year at a time changes only slightly. The differences in grouping lead to substantial changes in the components of expenditure growth. In particular, the continuously grouped sample shows growth primarily in treated prevalence, with a limited growth in the MCE. The high treated prevalence growth rate for the continuously grouped claims may be accounted for by an increase in low severity illnesses. For example, in the case of high cholesterol conditions, drug expenditures to treat high cholesterol may not always coincide with a visit to a

[15] This is the default and recommended method for allocation for Optum's ETG Symmetry Grouper.

[16] This may be important since expenditures prior to death may be extremely high. The estimates are based on a fixed sample of enrollees. Therefore, individuals observed in the last year of the data, 2007, could potentially die the following year, but those observed in 2003 are guaranteed to live at least four more years.

doctor, since they may have been diagnosed in a previous year. Consequently, when a doctor visit is not observed, then there is not an anchor record to establish treatment for high cholesterol. However, when looking at more years of data, it is possible to associate ungrouped expenditures with a visit to a doctor from previous years, leading to a growth in prevalence that is an artifact of continuous grouping with additional years of data. In contrast, when the data is grouped one year at a time, all information on the patients is viewed symmetrically across years, and we find that the growth is split more evenly between the MCE and $PREV$, as observed with the full sample.

3. *Expenditure per capita growth and other expenditure statistics may help select among methods.* Looking at disease-price inflation alone can be misleading, since many factors may lead to differences in disease-price growth. Additional statistics about expenditures and the population may be useful for selecting among different approaches to determine if an approach is valid and meets the researcher's objectives. For instance, in prior work we found that expenditures per capita may change based on the demographics of the population and the data contributors, which we found could affect $PREV$ and MCE (see Dunn, Liebman and Shapiro (2014)). For this reason, we use a sample of fixed data contributors and control for the demographics of the population by applying population weights. As another example, looking at the share of expenditures grouped over time may be a signal of other problems, as shown in the case of applying the ETG Symmetry grouper continuously in Table 6. In contrast, we found that there were relatively small trends in the share of expenditures grouped across the different methodologies, suggesting a limited potential impact on disease-price inflation. In general, producing additional figures may be useful, since they may be used to check with other external benchmarks (e.g., expenditure figures from National Health Expenditure Accounts or Bureau of Economic Analysis, or price figures from the Bureau of Labor Statistics).

Although looking at other statistics may be useful, it is important to highlight that the MCE should be viewed as the appropriate measure of inflation and focusing on episode counts may be problematic. The reason is straightforward - the MCE controls for the disease of the patient and focusing on treated prevalence will be highly sensitive to the health of the population. This can be seen in Dunn, Liebman and Shapiro (2013), which shows that using fixed demographics or allowing demographics of the population to change primarily affects $PREV$, not the MCE.

4. *There are important trade-offs when selecting the level of aggregation for a disease episode.* A key advantage of highly disaggregate disease categories is that researchers are able to examine more homogeneous episodes of a condition. That is, we view more disaggregate disease categories that control for severity to be more precisely defined and measured and more disaggregate measures are less likely to be affected by unobserved health. For instance, a

nice feature of both the ETG and MEG groupers applied in this paper is that they each classify several hundred disease episodes and they both have methods for accounting for severity adjustment.

On the other hand, there are some potential disadvantages to having highly disaggregate disease categories. One potential issue is that using highly disaggregate categories may be difficult for researchers trying to understand trends, since for some categorization systems there are potentially thousands of diseases (e.g., ICD-9 categories). In addition, when there are many disease categories, there will be fewer patients with each disease, potentially leading to small sample sizes for some diseases. Another issue is that more disaggregate categories could be more susceptible to changes in the coding practices of physicians.

One reason to consider more aggregate categories is when thinking about quality adjustment. For example, hypertension and heart disease are considered separate diseases by many grouping methodologies. However, the two diseases are closely related, since not treating hypertension can lead to heart disease. Therefore, the quality of treatment for hypertension has a direct effect on the prevalence of heart disease and also outcomes for patients that develop heart disease. For this reason, researchers may want to consider these disease categories together when considering how to measure the quality of treatment. More generally, additional work is needed to better understand how to intersect expenditures on treatments with measures of quality.

6 Conclusion

This paper viewed a variety of methods for analyzing and measuring disease-price inflation. While disease-price inflation is affected by the selected methodology, the various estimates appear to fall into a similar range in the aggregate. However, the disease-price inflation figures at the disease category level appear to be more sensitive to the selected methodology, although some similar general patterns emerge across methodologies. For instance, disease prices for cardiology-related conditions are rising more slowly than average, while expenditures and disease prices for preventative services are rising rapidly.

This paper demonstrates the effect of different approaches for allocating disease expenditures on disease-price inflation, but there is still a significant amount of work to conduct in the future. First, although many approaches were tried in this paper, there may be other methodologies for allocating disease expenditures not considered here that deserve further research. Second, the analysis here was conducted on a commercially-insured population over a relatively short time period. It may be useful to examine the effects of alternative methodologies on disease prices

when looking at other data sets, populations, and time periods. Hopefully, this paper can be a useful guide for these types of investigations in the future. Third, a critical area of future research will be to connect disease-price changes to quality changes. In this case, the selection of the most appropriate expenditure allocation methodology may depend on how quality and disease expenditure information are linked.

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7 Appendix

Table A1.1 Top Ten MEG Disease Categories Mapped to ETG Classification

MEG	Total Expenditures (millions)	ETG	% Exp. Of MEG on ETG	Cumulative % Exp. of MEG on ETG
Encounter for Preventive Health Services	$22,510	Routine exam	55.5%	55.5%
Encounter for Preventive Health Services		Ungroupable Medical Claims	13.1%	68.6%
Encounter for Preventive Health Services		Isolated signs, symptoms & non-specific diagnoses or conditions	6.1%	74.7%
Encounter for Preventive Health Services		Gastroenterology diseases signs & symptoms	4.8%	79.5%
Delivery, Vaginal	$21,831	Pregnancy, with delivery	95.2%	95.2%
Delivery, Vaginal		Uncomplicated neonatal management	1.3%	96.5%
Delivery, Vaginal		Other neonatal disorders, perinatal origin	0.9%	97.4%
Delivery, Vaginal		Ungroupable Medical Claims	0.7%	98.0%
Angina Pectoris, Chronic Maintenance	$15,560	Ischemic heart disease	86.0%	86.0%
Angina Pectoris, Chronic Maintenance		Hypertension	2.6%	88.6%
Angina Pectoris, Chronic Maintenance		Hyperlipidemia, other	2.3%	90.8%
Angina Pectoris, Chronic Maintenance		Ungroupable Medical Claims	1.6%	92.4%
Essential Hypertension, Chronic Maintenance	$14,132	Hypertension	70.9%	70.9%
Essential Hypertension, Chronic Maintenance		Ischemic heart disease	3.4%	74.3%
Essential Hypertension, Chronic Maintenance		Ungroupable Medical Claims	2.7%	77.0%
Essential Hypertension, Chronic Maintenance		Other disorders of ear/nose/throat	2.0%	79.0%
Neoplasm, Malignant: Breast, Female	$11,933	Malignant neoplasm of breast	92.9%	92.9%
Neoplasm, Malignant: Breast, Female		Ungroupable Medical Claims	1.6%	94.5%
Neoplasm, Malignant: Breast, Female		Malignant central nervous system metastases	0.7%	95.2%
Neoplasm, Malignant: Breast, Female		Non-malignant neoplasm of female genital tract	0.6%	95.9%
Osteoarthritis, Except Spine	$11,372	Joint degeneration, localized - knee & lower leg	60.0%	60.0%
Osteoarthritis, Except Spine		Joint degeneration, localized - shoulder	4.2%	64.3%
Osteoarthritis, Except Spine		Joint derangement - knee & lower leg	3.5%	67.8%
Osteoarthritis, Except Spine		Joint degeneration, localized - hand, wrist & forearm	3.3%	71.2%
Other Arthropathies, Bone and Joint Disorders	$11,178	Ungroupable Medical Claims	11.5%	11.5%
Other Arthropathies, Bone and Joint Disorders		Joint derangement - knee & lower leg	8.8%	20.3%
Other Arthropathies, Bone and Joint Disorders		Orthopedic signs & symptoms - unspecified	5.8%	26.1%
Other Arthropathies, Bone and Joint Disorders		Orthopedic signs & symptoms - knee & lower leg	5.5%	31.6%
Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance	$11,097	Diabetes	76.5%	76.5%
Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance		Ungroupable Medical Claims	3.8%	80.3%
Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance		Hyperlipidemia, other	2.9%	83.2%
Diabetes Mellitus Type 2 and Hyperglycemic States Maintenance		Hypertension	1.4%	84.6%
Osteoarthritis, Lumbar Spine	$9,778	Joint degeneration, localized - back	63.4%	63.4%
Osteoarthritis, Lumbar Spine		Joint degeneration, localized - thigh, hip & pelvis	25.4%	88.8%
Osteoarthritis, Lumbar Spine		Joint degeneration, localized - neck	1.4%	90.2%
Osteoarthritis, Lumbar Spine		Ungroupable Medical Claims	1.4%	91.6%
Depression	$9,678	Mood disorder, depressed	69.0%	69.0%
Depression		Other neuropsychological or behavioral disorders	16.5%	85.4%
Depression		Mood disorder, bipolar	4.6%	90.1%
Depression		Psychotic & schizophrenic disorders	3.2%	93.3%

notes: Table A1.2 shows the top 10 disease categories based on expenditure share for 2007. Four of the corresponding MEG categories are shown in order of highest allocation to lowest allocation.

Table A1.2 Top Ten ETG Disease Categories Mapped to CCS Classification

ETG	Total ETG Expenditures (millions)	CCS	% CCS on ETG	Cumulative % CCS on ETG
Ischemic heart disease	$24,954	Coron athero	46.6%	46.6%
Ischemic heart disease		Acute MI	17.9%	64.5%
Ischemic heart disease		No DX	10.2%	74.6%
Ischemic heart disease		Chest pain	7.0%	81.6%
Pregnancy, with delivery	$23,557	Nml preg/del	20.2%	20.2%
Pregnancy, with delivery		Ot compl bir	17.6%	37.8%
Pregnancy, with delivery		Prev c-sectn	11.5%	49.3%
Pregnancy, with delivery		OB-related perin	8.7%	58.0%
Joint degeneration, localized - back	$19,846	Back problem	77.4%	77.4%
Joint degeneration, localized - back		No DX	10.3%	87.7%
Joint degeneration, localized - back		Ot acq defor	3.5%	91.2%
Joint degeneration, localized - back		Ot bone dx	2.1%	93.3%
Diabetes	$19,189	No DX	59.1%	59.1%
Diabetes		DiabMel w/cm	15.7%	74.9%
Diabetes		DiabMel no c	12.7%	87.6%
Diabetes		Chest pain	1.1%	88.8%
Hypertension	$16,574	No DX	39.5%	39.5%
Hypertension		HTN	22.3%	61.8%
Hypertension		Chest pain	10.1%	71.9%
Hypertension		Htn complicn	4.8%	76.7%
Routine exam	$14,765	Exam/eval	40.7%	40.7%
Routine exam		Social admin	28.9%	69.6%
Routine exam		Other screen	11.5%	81.1%
Routine exam		Immuniz/scrn	6.2%	87.4%
Malignant neoplasm of breast	$14,168	Breast cancr	63.3%	63.3%
Malignant neoplasm of breast		Maint chem/r	12.6%	75.9%
Malignant neoplasm of breast		No DX	7.9%	83.8%
Malignant neoplasm of breast		Breast dx	4.6%	88.4%
Mood disorder, depressed	$10,327	No DX	43.7%	43.7%
Mood disorder, depressed		Mood disorders	41.0%	84.7%
Mood disorder, depressed		Anxiety disorders	4.2%	88.9%
Mood disorder, depressed		Adjustment	3.0%	91.9%
Joint degeneration, localized - neck	$9,051	Back problem	81.5%	81.5%
Joint degeneration, localized - neck		No DX	8.7%	90.2%
Joint degeneration, localized - neck		Ot bone dx	2.2%	92.3%
Joint degeneration, localized - neck		Ot conn tiss	2.0%	94.3%
Non-malignant neoplasm of female genital tract	$8,898	Bnign ut neo	28.1%	28.1%
Non-malignant neoplasm of female genital tract		Ot femal gen	17.0%	45.1%
Non-malignant neoplasm of female genital tract		Menstrual dx	13.6%	58.7%
Non-malignant neoplasm of female genital tract		Ovarian cyst	13.5%	72.1%

notes: Table A1.2 shows the top 10 disease categories based on expenditure share for 2007. Four of the corresponding CCS categories are shown in order of highest allocation to lowest allocation.

Table A5.1 MEG-based Decomposition by Major Diagnostic Category

Major Diagnostic Category	Expenditure Share (2007)	DECI	PREV	MCE
Musculoskeletal system Diseases and Disorders	17.7%	1.305	1.084	1.208
Gynocological Diseases and Disorders	11.2%	1.235	1.010	1.223
Cardiovascular System Diseases and Disorders	10.0%	1.110	0.999	1.107
Gastrointestinal Diseases and Disorders	9.1%	1.272	1.066	1.199
Neurological Diseases and Disorders	6.6%	1.262	1.052	1.202
Other contacts with Health Services	6.6%	1.526	1.189	1.273
Respiratory system Diseases and Disorders	5.3%	1.186	0.997	1.193
Ear, Nose, Mouth, and Throat Diseases	4.9%	1.066	0.965	1.107
Psychology	4.2%	1.170	1.093	1.066
Endocrine Diseases and Disorders	4.0%	1.409	1.221	1.168
Kidney and Urinary Tract Diseases	3.9%	1.240	1.342	0.977
Skin Diseases and Disorders	3.3%	1.277	1.108	1.157
Hematological Diseases and Disorders	2.3%	1.241	1.076	1.161
Hepatological Diseases and Disorders	2.2%	1.130	1.029	1.101
Nutritional Disorders	1.7%	1.076	1.303	0.861
Pediatrics	1.7%	1.196	1.021	1.183
Eye Diseases and Disorders	1.6%	1.212	1.123	1.081
Male Reproductive Diseases and Disorders	1.2%	1.273	1.184	1.156
Multiple Significant Trauma	0.8%	1.300	0.972	1.337
Infectious and Parasitic Diseases	0.8%	1.100	0.968	1.139
Immunodeficiency Diseases	0.6%	1.483	1.170	1.267
Dental	0.5%	1.283	1.071	1.198
Genetic Disorders	0.0%	0.948	1.082	0.872
Total Expenditures (in Billions) 2007	$554			

notes: Expenditures used to calculate expenditure share are calculated from the person-based decomposition.

Table A5.2 CCS-based Decompositions by ICD-9 Chapters

Description	Expenditure Share (2007)	DECI	PREV	MCE
Symptoms; signs; and ill-defined conditions	16.6%	1.763	1.310	1.310
Diseases of the circulatory system	10.5%	1.098	1.035	1.062
Diseases of the musculoskeletal system	10.2%	1.246	1.099	1.132
Endocrine; nutritional; and metabolic, immunity	7.4%	1.233	1.185	1.043
Diseases of the respiratory system	7.4%	1.096	0.979	1.123
Neoplasms	6.9%	1.289	1.057	1.251
Injury and poisoning	6.9%	1.178	0.993	1.187
Diseases of the nervous system and sense organs	6.5%	1.251	1.073	1.171
Diseases of the digestive system	5.8%	1.143	1.035	1.104
Diseases of the genitourinary systeem	5.1%	0.835	0.790	1.085
Mental illness	4.4%	1.219	1.084	1.121
Complications of pregnancy; childbirth	3.5%	1.227	1.075	1.149
Residual codes; unclassified	2.5%	1.469	1.203	1.218
Diseases of the skin and subcutaneous tissues	2.2%	1.278	1.080	1.186
Infectious and parasitic diseases	1.8%	1.427	1.150	1.183
Certain conditions originating in the perinatal period	1.1%	1.173	1.031	1.137
Congenital anomalies	0.8%	1.200	1.019	1.175
Diseases of the blood and blood-forming organs	0.3%	1.146	1.115	1.025
Total Expenditures (in Billions) 2007	$602			

notes: Expenditures used to calculate expenditure share are calculated from the person-based decomposition.