# **Appendix**

### **Applying the Different Approaches**

When applying the disease expenditure decomposition to the encounter-based approach or an episodebased 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  $ln(c_{i,t})=\beta_{0,t}+\sum_{d\in D_{i,t}}\beta_{d,t}I_{d,i,t}+v_{i,t}$ , where  $I_{d,i,t}$  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  $s_{d,i,t} =$ 

 $exp(\beta_{d,t})$  $\frac{exp(\mu a,t)}{exp(\sum_{d\in D_{i,t}}\beta_{d,t}I_{d,i,t})}$ . The total estimated expenditure that is allocated to diseases is computed as:  $c_{i,t}=exp(\beta_{0,t}+\sum_{d\in D_{i,t}}\beta_{d}I_{d,i,t}+v_{i,t})-exp(\beta_{0,t}+v_{i,t}).$  The estimated allocation of disease episode d for person i is then  $c_{d,i,t} = s_{d,i,t} \cdot c_{i,t}$ . With the estimate of  $c_{d,i,t}$ , 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,  $exp(\beta_0 + v_i)$ , 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  $c_{d,i} = s_{d,i} \cdot c_i$ . 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. Table A1. Top Ten MEG Disease Categories Mapped to ETG Classification



notes: Table A1 shows the top 10 MEG 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 A2. Top Ten ETG Disease Categories Mapped to CCS Classification



notes: Table A2 shows the top 10 ETG disease categories based on expenditure share for 2007. Four of the corresponding CCS categories are shown in order of highest allocation to lowest allocation.

## **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 A3. As a baseline, the first row of Table A3 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.<sup>1</sup> 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 the estimates in method 1.

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 categories of individuals: males above 50, males below 50, females above 50, and females below 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. Accounting for these major age and sex differences has only minor effects on the aggregate estimates.



Table A3. Growth Decomposition for 2003 to 2007 - Person-based Estimates

 $\overline{\phantom{a}}$ 

notes: The acronyms are: DECI - Demographically-Adjusted Expenditure Per Capita Index, PREV - Treated Prevalence Index, and MCE - Medical Care Expenditure Index.

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 allow 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 only one or two visits to a doctor for the treatment of hypertension within a year then hypertension will not be counted as a disease episode for that particular individual within the regression. This allocation method would 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.

# **More Lessons at the Disease Category Level**

Tables A4 and A5 show growth rates at the disease category level for both the MEG episode-based estimates and CCS person-based estimates. While the results show interesting trends for each categorization system, it is difficult to compare across CCS, MEG and ETG, because the disease categories are distinct.



#### Table A4. MEG-based Decomposition by Major Diagnostic Category

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

decomposition. The acronyms are :DECI - Demographically-Adjusted Expenditure Per Capita Index, PREV - Treated Prevalence Index, and MCE - Medical Care Expenditure Index

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



notes: Expenditures used to calculate expenditure share are calculated from the person-based decomposition. The acronyms are :DECI - Demographically-Adjusted Expenditure Per Capita Index, PREV - Treated Prevalence Index, and MCE - Medical Care Expenditure Index

Table A6 attempts to conduct a more direct comparison across methods. This table includes both ETG and 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 cannot compare these approaches precisely at the disease level. (Recall that they each have a distinct number of disease categories.) 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 refer to Tables A4 and A5-.



#### Table A6. Comparison ETG Decompositions with Non-ETG Methods

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. The acronyms are :DECI - Demographically-Adjusted Expenditure Per Capita Index, PREV - Treated Prevalence Index, and MCE - Medical Care Expenditure Index

# **Applying Episode Groupers Symmetrically Across Years**

 The episode-based estimates in the main text 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.<sup>2</sup> 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.<sup>3</sup> The results of the analysis are shown in Table A7.



Table A7. ETG Symmetry Grouper - Fixed Enrollee Sample

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 acronyms are :DECI - Demographically-Adjusted Expenditure Per Capita Index, PREV - Treated Prevalence Index, and MCE - Medical Care Expenditure Index

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 A7 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 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

 $\overline{a}$ 

 $^2$  This is the default and recommended method for allocation for Optum's ETG Symmetry Grouper.

 $3$  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.

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 for 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.