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The Rising Cost of Diabetes Care: Annual Variations in Expenditures, Decomposed by Price and Utilization

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Abstract

This project aims to analyze health care spending for patients with diabetes from 2006 to 2010. We begin by reviewing descriptive data on rising health care costs and the rising prevalence of diabetes nationwide, with a focus on the state of Florida. In our analysis, we use inpatient hospital data from Florida to construct an index that measures changes in health expenditures for diabetics. Based on these calculations, inpatient hospital spending on diabetes increased 23% for those insured by Medicaid, 25% for those insured by Medicare, and 10% for those with private insurance. We decompose these expenditure indexes into price and quantity components to understand whether increased spending is driven by higher prices or increased utilization. These indices are further broken down into age and sex cohorts. Overall we find significant variation in price and quantity changes, with the highest price increases for Medicaid recipients and greatest utilization increases for those with private insurance. Shifts in expenditures for females were generally driven by increased utilization, while shifts in expenditures for men were driven by price increases.

I. Introduction

Background

The problem of rising health care costs has received sustained national attention over the last ten years, becoming a key issue of public concern. Researchers have fueled this concern with books, journal articles, and essays that document the harmful effects of increased medical spending to individual welfare and the national budget. Over the past ten years, per capita medical expenditures have nearly doubled in the US, rising from $4,878 to $8,402 (Martin, et al. 2012). As a percentage of GDP, national health expenditures rose from 13.8 to 17.9 percent over that same time frame. Should these trends continue, our national health expenditures are projected to account for 19.8 percent of GDP by 2020, or $4.6 trillion per year (up from $2.6 trillion in 2010) (Keehan, et al. 2011).

Despite these daunting costs, the US does not enjoy demonstrably better health care results. As two articles (Garber and Skinner 2008 and Anderson and Hussy 2001) document, the US does not perform better than other OECD countries on average, despite spending nearly 50% more than those countries on health care. As a nation we pay about 40% more for inpatient medical care than Finland, France and Italy (Koechlin, et al. working paper). Compared to the entire OECD, we pay $5,326 more per capita every year for health care (Pearson 2010).

Within this environment of rising health care costs for a host of diseases, increased spending on diabetes care is especially troubling. In 2010, we spent approximately $194 billion on diabetic and pre-diabetic care, spending that accounted for about 7% of total U.S. health spending (UnitedHealth 2010). By 2020, annual spending for diabetes care is expected to reach $500 billion, and prevalence is predicted to reach 15% of the U.S. adult population, up from 8.5% in 2010. This project aims to look at what exactly drives these spending increases for

diabetes care. By understanding why health care expenditures keep rising, we can hopefully act to curb these costs through market interventions, Medicaid or Medicare reforms, or public health measures. Thus there is considerable insight to be gained from analyzing these increases in spending for diabetes, with applicability to other chronic illnesses as well.

Within the US, Florida is a crucial state in which to study diabetes spending. First, the state has faced soaring diabetes rates over the last two decades. In the last fifteen years, the state's diabetes rate increased from 5.7 percent to 9.9 percent (Orlando Sentinel 2011). Florida has now become one of the top ten states in the US in terms of diabetes prevalence, despite ranking 29th in terms of obesity prevalence. The major contributing factor here is Florida's aging population: according to the 2010 census, Florida is the fifth oldest state. Further, Florida is one of the most ethnically heterogeneous states in the country (US Census 2010). Many epidemiological studies have shown that, on a population level, diabetes rates increase dramatically with age, Hispanic identity, and black race (American Diabetes Association 2012). These trends have been empirically supported in Florida as well (Macaluso, et al.). As America becomes more diverse, and as its population ages with the retirement of the baby-boomers, Florida may well serve as a preview of what America will look like in coming years.

Using Indices to Understand Medical Care Spending

Indices are simple ratios that measure how a figure changes over time compared to a given base year, and so they can be useful tools for tracking shifts in medical spending. Economists have traditionally used indices to look at how the cost of living changes for bundles of consumer goods. The most common form of this index is the Laspeyres index, which holds the bundle of goods constant in a base year but allows prices to change (Deaton and Muellbauer

1984). The resulting fraction shows the effective change in the cost of living due solely to price increases. The Consumer Price Index is a familiar Laspeyres type index.

Looking at medical expenditures at an aggregate level, it is straightforward to construct indices that tracks changes over time or across regions. We call these Medical Care Expenditure indices (MCEs) because they show how medical expenditures rise or fall compared to a given base year or region. A number of recent papers have constructed MCEs over different regions and for different diseases (see White 2012, Aizcorbe and Nestoriak 2010, and Dunn et al. 2011). These papers found that medical expenditures on average rise by close to 5% annually, though there is significant variation across regions and diseases.

MCEs are useful metrics for describing how our expenditures are shifting every year, but they do not provide insight into why health spending is rising. Expenditures could rise because hospitals charge more for the same procedures, or they could be rising because people simply consume more medical care. Alternatively, there could be changes in insurance coverage or changes in the composition of the patient population, among other explanations. However, the most obvious analysis of expenditures is to break them down into price and quantity components, accounting for severity of disease. The key challenge to using indices for this analysis is that medical services cannot easily be decomposed into price and quantity components. We have chosen to use the methodology of Dunn, Shapiro, and Liebman (2011) to deconstruct our MCEs into price indices and quantity (i.e. utilization) indices. Using this method, we can see the degree to which spending shifts are caused by changes in price or utilization.

II. Methodology

Our data consists of inpatient records for hospitals in Florida in 2006 and 2010. First, we separate out diabetics from the rest of the patient pool. Next, we group these individuals by primary insurance type: Medicare, Medicaid, or private insurance companies. We further separate each insurance group by sex and age so that we have eight different age-sex cohorts in each insurance group. For each of these samples, we construct three indices (expenditure, price, and utilization) using the methodology of Dunn, Shapiro and Liebman (2011).

Identifying Diabetes Patients

We follow the straightforward method of choosing diabetics based on the principal diagnosis listed in the inpatient records. Because these records do not include personal medical data, we have to rely on the labels as filled out by hospitals. The disadvantage to this method is that it can often be difficult to identify a single diagnosis when a patient has co-morbidities. With that caveat in mind, we include individuals in our sample based on the principal diagnosis listed on their hospital record claim. These codes are the International Classification of Disease (ICD-9) codes, which assign code 250 to Diabetes mellitus.

Finding Total Spending

For private insurers, hospitals provide a "sticker price" of total charges of each record, but they actually collect payment from insurers based on pre-negotiated discount rates. In our data, the sticker price is the field "total charges". However, it would be inaccurate to use the total charges field for private insurers because this is not actually the price paid by the insurance companies. Since the negotiated discounts between hospitals and insurers for each discharge are

private and not recorded in the data, we instead create an estimated aggregate discount rate that we apply uniformly to all private insurance records. Though this method does not exactly track discounts from each private insurance company, it gives a clearer view of price changes over the four-year window. This gives use our calculated *price* variable that we use for records with private insurers.

The amount hospitals charge Medicaid and Medicare for each service is pre-determined by the Center for Medicare and Medicaid Services (CMS) based on the medical procedure, the principal diagnoses, and the severity of the health problem. Calculating the total charges to Medicare and Medicaid is as straightforward as reading off the total charges amount for each record.

Constructing the Medical Care Expenditure Index

The first index we construct for each sample is the Medical Care Expenditure index (MCE). This index compares average expenditures in a year, t_i, to average expenditures in the base year, denoted t_b:

$$MCE_{t_i} = \frac{e_{t_i}}{e_{t_b}}.$$

Here e_{t_i} is computed by summing the total charges (for Medicare and Medicaid) and total prices (for private insurers) in a year (E_{t_i}), then dividing by the number of these patients in that year (N_{t_i}). This is very straightforward. Decomposing expenditures into price and quantity requires some more definitions and calculations, however.

Constructing the Service Price Index and the Services Utilization Index

Our next step is to decompose expenditures into price and utilization components and create a Service Price Index (SPI) and a Service Utilization Index (SUI). These are indices to measure changes in prices and quantities (as opposed to levels). To do this, we use the methods from Dunn, et al. (2011) to calculate quantity measures for inpatient hospital visits. The average price is then calculated as the total expenditures divided by the quantity of services for that category.

As mentioned above, it is difficult to separate price from quantity for many health services. This is because the market for health care is different than the market for, say, bicycles, where there is a distinct unit of consumption and a clear price paid by the consumer. Instead, the quantity of medical services provided during a visit can be ambiguous. Consider this situation: I am admitted to the hospital after feinting. My physician examines me and runs blood tests. After a night in the hospital, I am diagnosed with high blood pressure associated with Type 2 diabetes. My physician prescribes me the appropriate medication and I am discharged. It seems questionable to say that the unit of consumption here is one since this was a one-night stay at the hospital. But would it be better to describe the quantity as two, since the doctor 1) conducted an examination and 2) ran blood work? There is no single correct answer to this question, and every approach has unique pitfalls.

In our analysis, quantity is simply the average spending for each specific procedure. As a consequence quantity is measured in dollars, not counts of the units of service. The advantage if this approach is that is provides a way to account for differences in the intensity of service across different types of service, as reflected in spending. An alternative is to simply count the number of units of service. The disadvantage of this approach is that it does not account for the substantial heterogeneity in intensity across medical services.

We organize each claim by its ICD-9-CM procedure code, a unique four-digit number assigned to each service. These codes are used by all insurers, public and private, and all medical providers. For each ICD-9-CM procedure code and modifier, for a given year, we compute the arithmetic mean of total charges (or discounted charges for private insurers) for that procedure. This is $\bar{A}^o_c = \frac{\sum_{i=1}^{n} A^o_{ic}}{n}$, where A^o are total charges during inpatient stays, c indexes the ICD-9-CM procedure code, and i indexes the procedure (there are n procedures of that ICD-9-CM code in the data). To calculate the number of services provided in a hospital inpatient setting, we sum the mean allowed amounts for each unique ICD-9-CM plus modifier. The total number of services provided is the sum of these mean charges (prices for private insurers), and is $\bar{A}^o - \sum_{c=1}^{C} \bar{A}^o$.

We calculate the average price by dividing total expenditures by quantity. Thus, in a given year t_i, we have total quantity, $\bar{A}^s_{t_i}$, average price, $p^s_{t_i}\left(= E^s_{t_i}/\bar{A}^s_{t_i}\right)$, and the number of diabetics in our sample, N_{t_i}. Let $q^s_{t_i} = \bar{A}^s_{t_i}/N_{t_i}$ denote the utilization of a service in a given year, and let e_{t_i} denote average diabetes expenditures in a given year (calculated as total expenditures divided by N_{t_i}). With these values, we construct a Medical Care Expenditure index (MCE, previously defined above), a service price index (SPI), and a service utility index (SUI) as follows (with t_b representing the base year):

$$MCE_{t_i} = \frac{e_{t_i}}{e_{t_b}} \qquad SPI_{t_i} = \frac{\sum_s p^s_{t_i} \times q^s_{t_b}}{\sum_s p^s_{t_b} \times q^s_{t_b}} \qquad SUI_{t_i} = \frac{\sum_s p^s_{t_b} \times q^s_{t_i}}{\sum_s p^s_{t_b} \times q^s_{t_b}}$$

After calculating these three indices for all patients in our sample, we construct the same indices for eight different sex and age groups. We create separate groups for males and females in the following age cohorts: 18-34, 35-49, 50-64, and 65 and older. These groups serve as

proxies for severity of disease, with the presumption that men are on average more ill than women, as are older compared to younger diabetics. These age cohorts are the most commonly used in the scientific literature[1] (other than cohorts by decade, which would make our samples too small). They track the general progression of the disease as it becomes more severe, and they are centered at about the average age of diagnosis, which was 52 in 2008 (Centers for Disease Control and Prevention 2008). Thus, in this analysis there are eleven three-index sets for insurance group (one set for the entire sample, one set for all males, one set for all females, and one set for each of the eight age-sex cohorts). Each three-index set is composed of an MCI, SPI, and SUI.

III. Data

For this analysis we use hospital inpatient data from the Florida Agency for Health Care Administration, specifically the Florida Center for Health Information and Policy Analysis. The inpatient data files were collected from all hospitals including short-term and long-term psychiatric and comprehensive rehabilitation centers, and they list demographic information, diagnoses, procedures, charges, and the principal payer, among other categories.

Each observation corresponds to one inpatient stay at a hospital, with a unique System Record ID Number. Each record may have multiple diagnoses from different times in a patient's hospital stay, but we exclusively look at the principal diagnosis, which reflects the diagnosis determined to be chiefly responsible for admission.

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[1] These are some of the articles and a book that use these same age cohorts: Quilliam, et al. (2011); Ortiz, et al. (2011); Wang, et al. (2003); and Aubert (1995) p. 88.

In total, we dealt with 2,213,187 records from 2006 and 2,516,384 records from 2010. We selected the data first for diabetes patients, then for those that had a principal procedure listed in the records:

Number of Records in the Data
(Table 1)

	Records	**Diabetics**	**Diabetics with *prin_proc***
Medicaid 2006	429746	4828	1392
Medicare 2006	1060922	14819	6130
Private 2006	722519	7077	2141
Medicaid 2010	555707	7730	2760
Medicare 2010	1272861	19542	9344
Private 2010	687816	7549	2773

The data were analyzed as text files that we ran through a program we wrote in in the Python programming language.

IV. Results

Tables 2 through 4 (below) show the MCE, SPI, and SUI for each age-sex cohort using 2006 as the base year. These numbers show the relative change in expenditures, price, and utilization (respectively) for each sample from 2006 to 2010. For example, for all Medicare recipients the MCE is approximately 1.23. This means that expenditures for diabetics on Medicaid rose by 23% from 2006 to 2010. In Tables 5 through 7 we report the annualized growth rate implied by the 4-year figures in Tables 2 through 4. Thus the 23% growth rate in expenditures from 2006 to 2010 for Medicaid recipients implies that expenditures grew at an annual rate of 5.3%.

The MCEs in Table 2 range from 0.666 for the youngest cohort of male Medicaid recipients to 1.672 for the oldest cohort of male Medicaid recipients. The price indices, the SPIs, have a larger range. They fall as low as 0.698 for all females with private insurance and reach as high as 1.872 for male Medicare recipients in the youngest cohort. Utilization increased the most for the youngest cohort of female Medicaid recipients, with an SUI of 1.741, and utilization fell most for the youngest mail cohort, with an SUI of 0.377.

We see that overall increases in expenditures can be ascribed to either price or utilization increases depending on the population examined. In general, though, patterns emerged for price and utilization shifts for each insurance group. Prices increased the most for Medicaid recipients, increased by a smaller amount for Medicare recipients, and fell for individuals with private insurance. Meanwhile utilization fell for Medicaid recipients, grew for Medicare recipients, and grew the most for those with private insurance.

There are also significant differences between the male and female populations. Almost universally, increases in expenditures for females were driven by increased utilization, while for men increased expenditures were almost always due to increased prices. Comparing male and female Medicaid recipients makes this distinction stark. For females, expenditures increased by 29% because quantity increased by 46% (and despite prices falling to 88% of their 2006 levels). Meanwhile for males, expenditures increased 13% because prices increased 68%, while quantity decreased to 68% of its original level in 2006.

Martin, et al. (2012) found that Medicare spending grew 7% in 2009 and 5% in 2010, results that are consistent with our sample's 5.66% annual growth rate for Medicare recipients. Their article also found Medicaid spending grew by 8.9% in 2009 and 7.2% in 2010, while we found Medicaid expenditures rose by 5.30% annually between 2006 and 2010. For privately

insured individuals, Martin, et al. (2012) found that health expenditures rose by 1.57% per year, less than the annual rate from our sample, which was 2.48%. The recession is one likely contributing factor to the discrepancy between their figures and ours in private growth rates. The recession only started in 2008, and as Martin, et al. (2012) note depressed household incomes, uncertainty about the future, and less insurance coverage all led to decreased demand for medical services.

White (2012) found that for her sample of privately insured autoworkers, price variations accounted for about 35% of regional differences in expenditures, while quantity changes accounted for the remaining 65%. This is consistent with our findings for privately insured individuals, where utilization shifts (when aggregated over both sexes) fueled expenditure shifts more than price shifts.

Table 2 **Medicaid Indices (4-year)**

Type	Sex	Age Cohort	MCE	SPI	SUI
Medicaid	Both	All	1.230	1.347	0.913
	Female	All	1.290	0.876	1.455
		Cohort 1	1.501	0.862	1.741
		Cohort 2	1.225	0.747	1.639
		Cohort 3	1.293	0.995	1.299
		Cohort 4	0.796	1.042	0.764
	Male	All	1.126	1.675	0.672
		Cohort 1	0.666	1.766	0.377
		Cohort 2	1.177	1.697	0.694
		Cohort 3	1.179	1.409	0.837
		Cohort 4	1.672	1.034	1.618

Table 3		Medicare Indices (4-year)			
Type	**Sex**	**Age Cohort**	**MCE**	**SPI**	**SUI**
Medicare	Both	All	1.246	1.104	1.129
	Female	All	1.295	1.009	1.284
		Cohort 1	1.334	0.872	1.530
		Cohort 2	1.232	1.212	1.016
		Cohort 3	1.275	1.032	1.235
		Cohort 4	1.314	0.887	1.481
	Male	All	1.202	1.264	0.951
		Cohort 1	1.328	1.872	0.710
		Cohort 2	1.066	1.216	0.877
		Cohort 3	1.100	1.133	0.971
		Cohort 4	1.272	1.326	0.960

Table 4		Private Indices (4-year)			
Type	**Sex**	**Age Cohort**	**MCE**	**SPI**	**SUI**
Private	Both	All	1.103	0.948	1.163
	Female	All	1.170	0.698	1.675
		Cohort 1	0.720	1.084	0.664
		Cohort 2	1.270	0.722	1.759
		Cohort 3	1.273	0.713	1.787
		Cohort 4	0.878	0.854	1.029
	Male	All	1.068	1.221	0.875
		Cohort 1	0.981	1.274	0.770
		Cohort 2	1.084	0.855	1.268
		Cohort 3	1.037	1.230	0.843
		Cohort 4	1.390	1.051	1.323

Table 5		Medicaid Annualized Growth Rates (%)			
Type	**Sex**	**Age Cohort**	**MCE**	**SPI**	**SUI**
Medicaid	Both	All	5.303	7.738	-2.260
	Female	All	6.580	-3.246	9.834
		Cohort 1	10.690	-3.643	14.875
		Cohort 2	5.201	-7.021	13.144
		Cohort 3	6.637	-0.122	6.767
		Cohort 4	-5.551	1.030	-6.515
	Male	All	3.008	13.765	-9.456
		Cohort 1	-9.670	15.284	-21.645
		Cohort 2	4.158	14.133	-8.740
		Cohort 3	4.202	8.955	-4.363
		Cohort 4	13.710	0.829	12.775

Table 6		Medicare Annualized Growth Rates (%)			
Type	**Sex**	**Age Cohort**	**MCE**	**SPI**	**SUI**
Medicare	Both	All	5.655	2.493	3.085
	Female	All	6.686	0.231	6.439
		Cohort 1	7.471	-3.372	11.222
		Cohort 2	5.353	4.931	0.403
		Cohort 3	6.253	0.800	5.409
		Cohort 4	7.068	-2.944	10.316
	Male	All	4.709	6.039	-1.254
		Cohort 1	7.358	16.967	-8.216
		Cohort 2	1.613	5.000	-3.225
		Cohort 3	2.415	3.162	-0.724
		Cohort 4	6.205	7.307	-1.027

Table 7		Private Annualized Growth Rates (%)			
Type	**Sex**	**Age Cohort**	**MCE**	**SPI**	**SUI**
Private	Both	All	2.484	-1.316	3.851
	Female	All	3.998	-8.582	13.760
		Cohort 1	-7.895	2.029	-9.726
		Cohort 2	6.164	-7.817	15.166
		Cohort 3	6.227	-8.123	15.619
		Cohort 4	-3.191	-3.869	0.706
	Male	All	1.661	5.112	-3.282
		Cohort 1	-0.471	6.234	-6.311
		Cohort 2	2.048	-3.831	6.114
		Cohort 3	0.915	5.307	-4.170
		Cohort 4	8.583	1.246	7.247

V. Conclusions

Our analysis on the aggregate level supports the work of other researchers showing an approximate annual growth rate in medical expenditures of 5%. However our finer, cohort-level analysis shows a more nuanced picture that points to different strategies for containing costs.

The Martin, et al. (2012) article shows how medical care utilization has risen at a slower pace since the 2008 recession. According to the this article, utilization increases accounted for 1.3% of the 5% increase in personal health care spending from 2007 to 2009. This is a much smaller contribution than from 2000 and 2006, when utilization increases accounted for 3.3% out of 7.6% increases in overall health spending. Our analysis shows that this decrease in utilization growth is probably driven by men (at least among Floridian diabetics).

Meanwhile, our analysis of women in our sample leads us to agree with White (2012): to control spending growth, we should focus not only on price controls, but also on improving patient health. From 2006 to 2010, female utilization increased almost uniformly, despite the recession. Part of this is likely due to increased incidence of diabetes among females over this time: the CDC reports that from 2006 to 2010, the prevalence of female diabetics rose faster than the prevalence for men. Our analysis cannot show how much this increased incidence impacted utilization, but it is safe to say that curbing the spread of diabetes for females will significantly help reduce money spent on diabetes management.

In sum, these results depict a complex underpinning to the typical MCE analysis. Though expenditures are rising steadily, there is no single explanation that is applicable across the spectrum. For Medicare and Medicaid recipients, these increases appear to be largely driven by costs. For those with private insurance, increases are driven by utilization increases. Accordingly, we recommend a similarly heterogeneous strategy for curtailing costs for diabetes in the future that includes price management for Medicare and Medicaid recipients, and stronger public health campaigns to help curb incidence of diabetes among women.

REFERENCES

Aizcorbe, A. and Nestoriak, N. 2011. ”Changing Mix of Medical Care Services: Stylized Facts and Implications for Price Indexes”, Journal of Health Economics.

American Diabetes Association. "Diabetes Basics." Diabetes Statistics. American Diabetes Association, 2012. Web. 26 Apr. 2012. <http://www.diabetes.org/diabetes-basics/diabetes-statistics/?loc=DropDownDB-stats>.

Aubert, Ronald. *Diabetes in America*. [Bethesda, Md.]: National Institutes of Health, National Institute of Diabetes and Digestive and Kidney Diseases, 1995. Print.

"CDC's Diabetes Program - Data & Trends - Distribution of Age at Diagnosis of Diabetes among Adult Incident Cases Aged 18-79 Years, United States, 1980-2008." *Centers for Disease Control and Prevention*. N.p., n.d. Web. 26 Feb. 2012. <http://www.cdc.gov/diabetes/statistics/age/fig2.htm>.

Census Data 2010: Summary File –Florida. Prepared by the U.S. Census Bureau, 2011.

Deaton, Angus, and John Muellbauer. Economics and Consumer Behavior. Cambridge: Cambridge UP, 1980. Print.

Dunn, A., A. H. Shapiro, and E. Liebman, 2011. “Geographic Variation in Commercial Medical Care Expenditures: A Decomposition Between Price and Utilization.” Working Paper.

Garber, Alan M., and Jonathan Skinner. "Is American Health Care Uniquely Inefficient?" Journal of Economic Perspectives 22.4 (2008): 27-50.

Jameson, Marni. "Florida Ranks in Top 10 of States with High Diabetes Rates." Orlando Sentinel. June-July 2011. Web. 26 Apr. 2012. <http://articles.orlandosentinel.com/2011-07-14/health/os-florida-diabetes-20110713_1_obesity-and-diabetes-american-diabetes-association-obesity-rate>.

Keehan, S. P. "National Health Spending Projections through 2020: Economic Recovery and Reform Drive Faster Spending Growth." Health Affairs 30.8 (2011): 1594-605. Print.

Koechlin, Francette, Luca Lorenzoni, and Paul Schreyer. "Comparing Price Levels of Hospital Services Across Countries: Results of Pilot Study.” OECD Health Working Paper 53 (2010).

Martin, A.B., D. Lassman, B. Washington, A. Catlin, and the National Health Expenditure Accounts Team. Growth in US Health Spending Remained Slow in 2010; Health Share of Gross Domestic Product Was Unchanged from 2009. Health Affairs, 31, no. 1 (2012): 208-219

Ortiz AP, Romero C, Disdier O, Santana E, Torres M, Torres EA, Pérez CM. Diabetes is associated with chronic liver disease and liver cancer in the adult population of Puerto Rico. P R Health Sci J. 2011 Sep;30(3):132-4. PubMed PMID: 21932714.

Pearson, Mark. "Disparities in Health Expenditure across OECD Countries: Why Does the United States Spend so Much More than Other Countries?" Written Statement to Senate Special Committee on Aging (2009).

Quilliam BJ, Simeone JC, Ozbay AB, Kogut SJ. The incidence and costs of hypoglycemia in type 2 diabetes. Am J Manag Care. 2011 Oct;17(10):673-80. PubMed PMID: 22106460.

Reinhardt, U. E., P. S. Hussey, and G. F. Anderson. "Cross-National Comparisons Of Health Systems Using OECD Data, 1999." Health Affairs 21.3 (2002): 169-81.

Scitovski A, 1964. “An Index of the Cost of Medical Care – A proposed New Approach, in: S. J. Axelrod (Ed.), The Economics of Health and Medical Care, Universeity of Michigan, Bureau of Public Health Economics, Ann Arbor: 128-148.

Wang CS, Wang ST, Yao WJ, Chang TT, Chou P. Community-based study of hepatitis C virus infection and type 2 diabetes: an association affected by age and hepatitis severity status. Am J Epidemiol. 2003 Dec 15;158(12):1154-60. PubMed PMID: 14652300.

White, Chapin, 2012. “Health Status and Hospital Prices Key to Regional Variation in Private Health Care Spending.” Research Brief. National Institute of Health.