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SOCIAL DETERMINANTS OF HEALTH: THE IMPACT ON HEALTH OUTCOMES AND HOSPITAL PROFITABILITY

Abstract

Hospitals are experiencing decreasing profitability due to increasing healthcare cost. In this paper, I demonstrate that there is financial value to hospitals by addressing social determinants of health (SDOH) as this strategy improves health outcomes and yields cost savings. I estimate the impact of SDOH on the health outcomes using an IV probit regression analysis and estimated the impact of health outcomes on cost using a basic linear regression. I estimate that improving SDOH by one standard deviation will result in hospital cost savings as follows: addressing Violent Crime will decrease hospital cost between 0.16% and 0.21%, addressing Supplemental Nutrition Assistance program will decrease cost up to 0.5% and addressing Unemployment will decrease hospital cost between 1.2% and 1.7% resulting in a favorable impact on hospital profitability. I use the HCUP National Inpatient Sample 2014 dataset along with externally identified variables representing SDOH to estimate cost savings.

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I. Introduction

Healthcare costs have been consistently increasing every year since the 1960s. They account for nearly 17.5% of GDP as recent as 2018 and they are on a trajectory to top 20% of GDP by 2025 according to the Centers for Medicare and Medicaid Services (CMS)[1]. There are several factors that are attributing to the increases in healthcare costs and the erosion of hospital profitability including increases in general & administrative expenses, aging patient population, growing population, and more incidents of disease (Dielman et.al., 2017). Profitability is also being affected from a revenue perspective due to decreasing negotiated reimbursement rates from Commercial (e.g., private, employer) Payers (i.e., United Healthcare, Humana, Aetna, etc.) as a result of a shift from Fee-for-Service to Value Based Care models and rate reductions for services from Government Payers (i.e., Medicare and Medicaid).

Of the total population in the US, the individuals insured by the Government Payers accounts for the second largest portion of the patient mix for hospitals behind those that are insured by their employer which are primarily covered by commercial Payers (see Figure 1).

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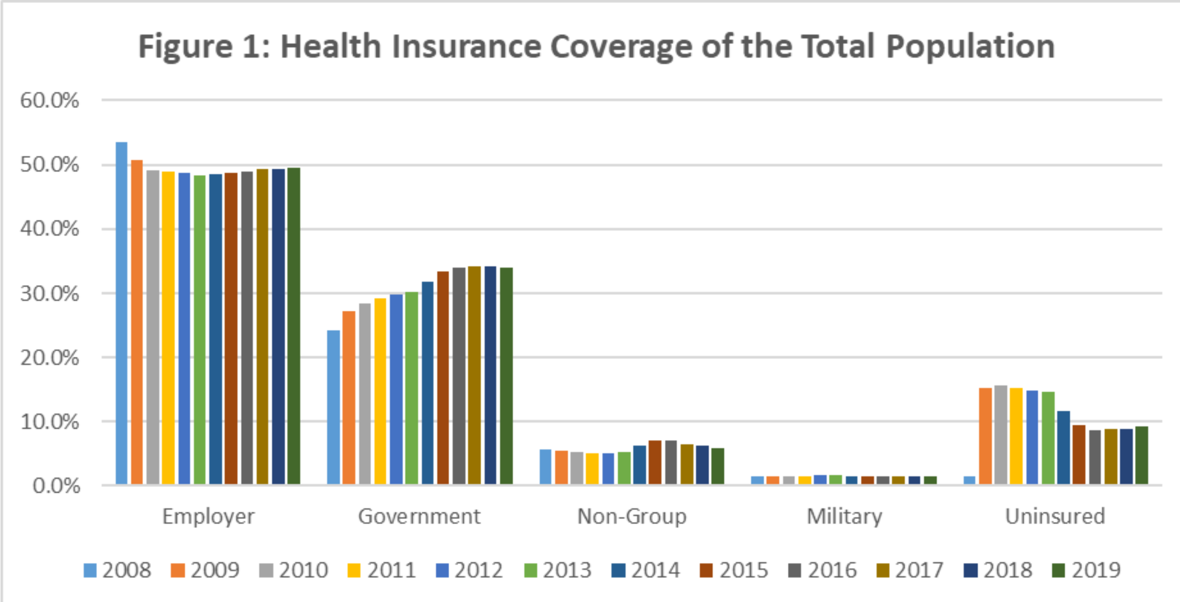
[1] National Health Expenditure Projections 2015-2025: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/NationalHealthExpendData/Downloads/Proj2015.pdf



Sources: KFF estimates based on the 2008-2019 American Community Survey, 1-Year Estimates. https://www.kff.org/state-category/health-coverage-uninsured/health-insurance-status/

Employer: Includes those covered through a current or former employer or union, either as policyholder or as dependent

Government: Includes those covered by Medicare, Medicare Advantage, and those who have Medicare and another type of non-Medicaid coverage where Medicare appears to be the primary payer. Excludes seniors who also report employer-sponsored coverage and full-time work, and those covered by Medicare and Medicaid (dual eligibles). Also includes those covered by Medicaid, Medical Assistance, Children's Health Insurance Plan (CHIP) or any kind of government-assistance plan for those with low incomes or a disability, as well as those who have both Medicaid and another type of coverage, such as dual eligibles who are also covered by Medicare.

Non-Group: Includes those covered by a policy purchased directly from an insurance company, etiher as policyholder or as dependent

Military: Includes those covered under the military or Veterans Administration

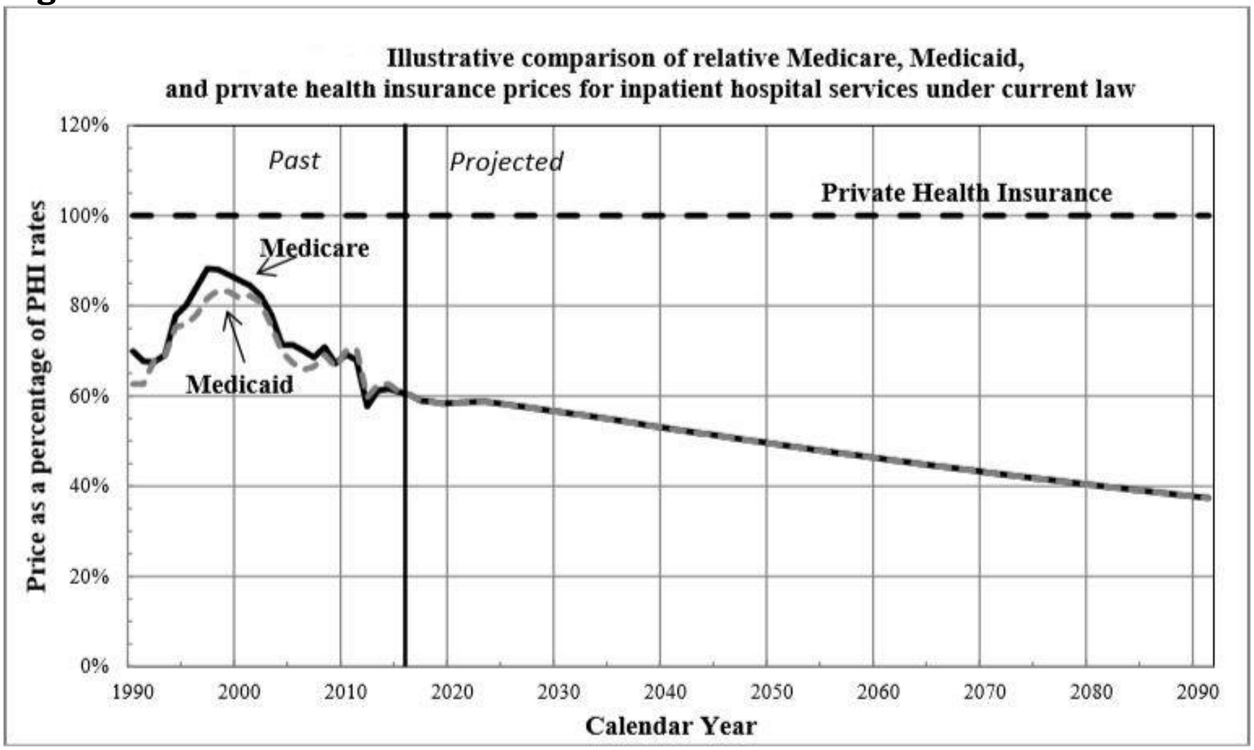
Uninsured: Includes those without health insurance and those who have coverage under the Indian Health Service only

Employer insured health expenditures have continued to grow consistently since 2013. According to the 2017 Healthcare Cost and Utilization report (2019), spending per capita reached $5,641 per person and increased by 16.7 percent over a five-year period, which was an all-time high for individuals covered by their employers. Fortunately, hospital reimbursement for services provided to individuals that are insured by their employers, is sufficient to cover the cost of care and therefore, does not have a negative impact on hospital profitability associated with Commercial Payers.

The number of uninsured people peaked right after the 2008 economic crisis and began to decrease in 2013 after the Affordable Care Act passed and was put into effect. Most of the reduction of the uninsured moved to the Government insured bucket as Medicare and Medicaid saw increases shortly after the passing of the Affordable Care act as well. These two groups include the oldest population (Medicare) and the poorest population (Medicaid) which accounts for higher costs per capita compared to individuals covered by their employers. In 2017, Medicaid reported the median healthcare expenditures per capita for people covered by Medicaid was $7,171 and $16,544 for people that were over the age of 65 (Medicaid.gov, n.d.). Unlike those that are insured by their employers, the hospital reimbursement for services provided to individuals insured by Government Payers are not enough to cover the cost of care. Additionally, people covered by Government Payers are primarily low-income and often do not have the funds to cover any additional out-of-pocket costs (i.e., deductibles, coinsurance, copays) which results in large increases in uncompensated care (i.e., write-offs) by hospitals.

Currently, hospitals are not being reimbursed sufficiently to cover the cost of care provided to the patients that are insured by Government Payers and trends reflect plummeting reimbursement rates for hospital services which adds to profitability erosion. The reduction in reimbursement rates for Government Payers are due to legislative restraints enacted as part of the Affordable Care Act (i.e., Value Based Care programs) and productivity adjustments (Department of Human Services, 2018). Figure 2 shows how Medicare and Medicaid reimbursement rates for services provided by hospitals are projected to decrease over the next several years as a percentage of private (Commercial) payers.

Figure 2:



Source: Department of Health and Human Services – CMS Office of the Actuary: https://www.cms.gov/Research-Statistics-Data-and-Systems/Statistics-Trends-and-Reports/ReportsTrustFunds/Downloads/2018TRAlternativeScenario.pdf

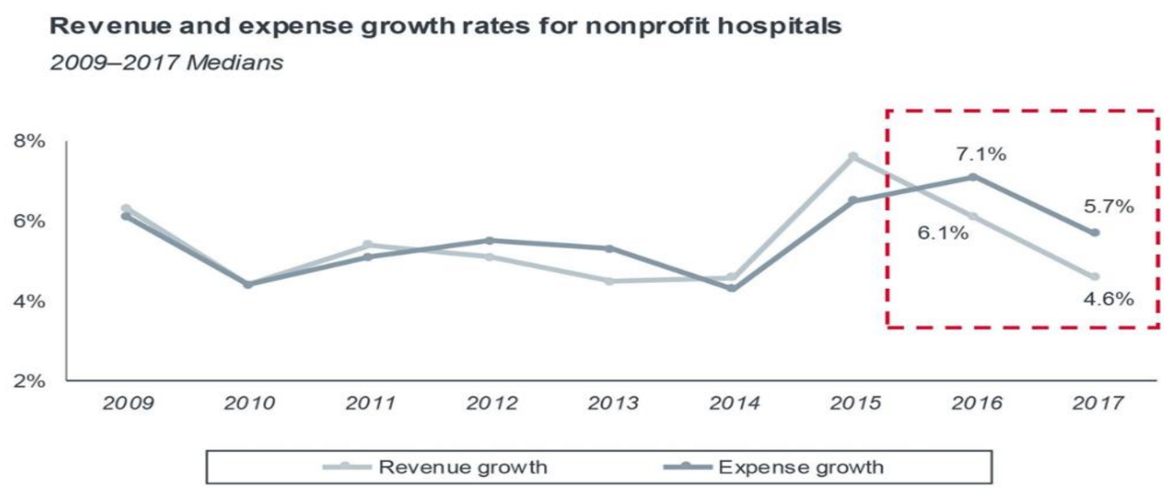
As the population demographic changes and more and more people are insured by Government Payers, CMS projects that over 80 percent of hospitals will lose money by treating Medicare and Medicaid patients. "By the end of the long-range projection period, Medicare and Medicaid payment rates for inpatient hospital services would both represent roughly 37 percent of the average level for private health insurance", (Department of Health and Human Services, 2018)

On the revenue side, Commercial Payers are following the lead of Government Payers and are shifting from fee-for-service reimbursement models to a Value Based Care models. The fee-for-service model reimburses hospitals based on the quantity of services they provide and individual patient utilization and cost, independent of health outcomes. Value Based Care put emphasis on health outcomes, and focuses on quality of services, population utilization and costs and incentivizes the hospitals by paying them bonuses for achieving the agreed upon quality measures through Pay-For-Performance, at-risk and shared savings arrangements, and penalties (Baker Tilly, 2016). This shift is prompting the Payers to decrease negotiated reimbursements rates on the front-end and instead expect hospitals to appropriately manage the care of the patient by providing high quality service and keeping cost low and being compensated with bonuses on the backend. However, all hospitals and providers have not fully adopted the new Value Based model and are still administering care more in line with fee-for service (Sokol, 2020). Hospitals are billing procedures (i.e., surgeries) based on per units of service or item required for overall procedure versus pricing more services in bundled payments[2] where all procedures are included in one rate which forces the hospitals to assume more risks. Additionally, approximately 52.5 percent of hospitals are paying doctors straight salary and 31.8 percent of hospitals are paying doctors based on their personal productivity which is consistent with fee-for-service payment models and only 13.1 percent are paid based on the hospital's financial performance and bonuses which is consistent with Value Base Care model (Rama, 2018). This is resulting

[2] According to the American Hospital Association, "bundled payment programs generally provide a single, comprehensive payment that covers all of the services involved in a patient's episode of care"

in lower upfront revenue and increased cost because hospitals have not strategically kept pace with the direction Payer reimbursement models are going, and it is creating a large gap between the cost of care and the reimbursement for care of patients. Figure 3 highlights our current healthcare environment, where we see healthcare revenue increasing, but at a decreasing rate compared to prior years. Also, healthcare cost is increasing at a faster rate than healthcare revenue. As a result, hospitals are seeing profitability erode.

Figure 3:



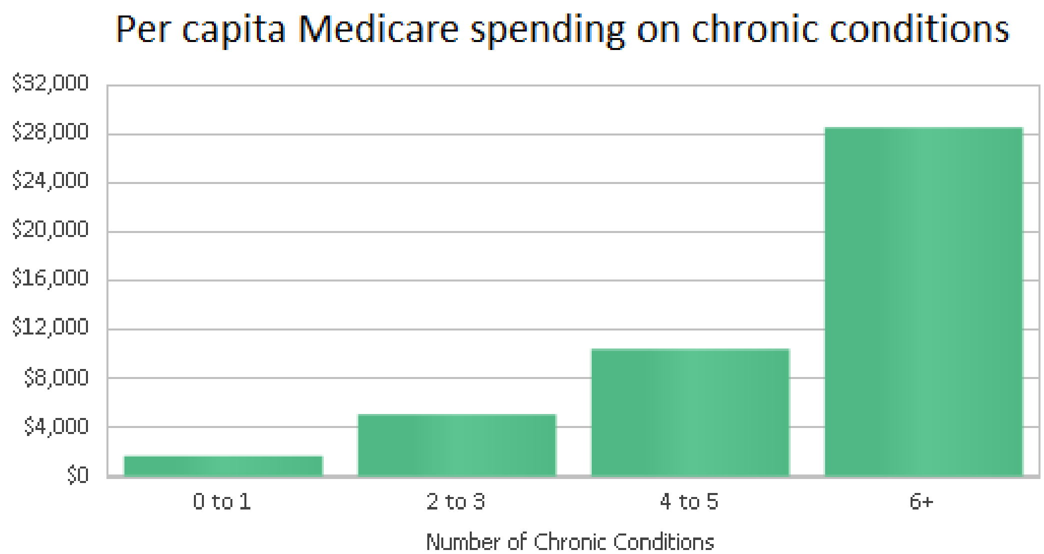
Source: Modern Healthcare: https://www.modernhealthcare.com/finance/3-hallmarks-cost-disciplined-health-system-and-profiles-success

Hospitals are running out of ways to increase revenue in their quest to combat decreased profitability. Simply attempting to negotiate higher rates with Payers is no longer sufficient. The profitability erosion problem needs to be addressed through direct medical cost starting with the hospitals. There are other areas of a health system[3] that attributes to increasing healthcare costs, but the focus in this paper is hospital care as it accounts for approximately 32.7% of healthcare spending, compared to 15.5% for physician services, 9.2% for prescription drugs, 4.4% for clinical services, 4.6% for skilled Nursing, 2.8% for home health care and 15.1% for other personal health care (Rama, 2020).

There appears to be opportunity to decrease hospital cost by focusing on high-risk chronic patients that are covered by Government Payers because their reimbursement rates are low and often do not cover the cost of providing the services. There are many patients that are on Medicaid or Medicare that have multiple chronic conditions. "While just seventeen percent of Medicare patients live with more than six chronic conditions, they account for half of all spending on beneficiaries with chronic disease" (Bresnik, 2016). Figure 4 shows the variation in Medicare spending per capita based on the number of chronic conditions present.

[3] Hospitals within the Health System is the focus of this paper. The Agency for Healthcare Research and Quality (AHRQ) defines Health Systems as, "an organization that includes at least one hospital and at least one group of physicians that provides comprehensive care (including primary and specialty care) who are connected with each other and with the hospital through common ownership or joint management

Figure 4:



Source: Health IT Analytics: https://healthitanalytics.com/news/analyzing-medicare-chronic-disease-prevalence-spending-rates

Over the years, hospitals have seen costs increase due to patients getting sicker and older and requiring more emergency room or inpatient hospital stays. Hospitals could reduce some of the cost by addressing the social determinants that are causing these high-risk chronic patients to be admitted to the hospital in the first place.

Per the Centers of Disease Control, conditions in places where people live, learn, work and play affect a wide range of health risks and outcomes. These conditions are known as social determinants of health (SDOH). SDOH has been associated with various causes of health issues over the years. The concept of SDOH was first introduced in the 1960's under President Lyndon B. Johnson through US Policies designed to declare war on poverty which introduced Medicaid, Medicare, Welfare (i.e., food stamps), Job Corps and Head Start Programs (Johnson, 2018 p.5). The creation of these programs was indicative of a correlation between a person's living environment and their ability to maintain good health.

This paper aims to test the extent to which SDOH causes unfavorable health outcomes (evidenced by comorbidities) resulting in higher hospital cost. Additionally, I show that improving SDOH by one standard deviation will result in hospital cost savings, thereby, improving profitability. To do this, I regress hospital cost against comorbidities and specific key control variables (length of stay, Payer, Hospital Control, Hospital Bed Size and Service Lines) to determine the incremental cost associated with a patient with comorbidities. I also perform an instrumental variable probit regression where each comorbidity is regressed against the three SDOH endogenous variables, Violent Crime, Supplemental Nutrition Program distribution, and Unemployment while controlling for other comorbidities, race, gender, household income, and hospital location. Political Affiliation is used as an instrument in the IV regression since it is correlated with the SDOH, but uncorrelated with the comorbidities. That incremental cost of the comorbidity from the linear regression and the causal impact of the SDOH on the comorbidity from the IV regression is used to calculate the cost savings generated from improving each SDOH by one standard deviation. I estimate total hospital cost will decrease between 0.16% and 0.21% for Violent Crime improvements, up to 0.5% for Supplemental Nutrition Assistance Program improvements and between 1.2% and 1.7% for unemployment improvements resulting in a favorable impact on hospital profitability. I also repeat the basic linear regression on hospital cost and the IV regression on the comorbidities on a subset of the dataset that consists of all observations containing DRG 470 – Major Joint Replacement without Major Complications. This micro analysis is done to determine if the correlation and causation of SDOH to hospital cost is still present.

This paper is organized as follows: The second section summarizes previous empirical and theoretical research related to eroding hospital profitability and the impact on SDOH on health outcomes. The third section presents detail on the primary source data used to analyze the relationships of health outcomes and SDOH. The fourth section presents the data methods used including the econometric models and the cost savings calculations. The fifth section describes the empirical results. Section six suggests future research possibilities because of some of the constraints of the dataset. The seventh section discusses how health systems can change processes and influence policies to implement initiatives to improve SDOH resulting in improved profitability. Section 8 is the conclusion.

II. Literature Review

In this section, I review some literature related to hospital profitability and its erosion over time. Additionally, I review previous research that focuses on Medicaid patients or low-income patients and how treatment of those patients correlates to decreasing profitability

Hospital Profitability

Hospitals have been faced with finding ways to stay profitable for all lines of business. Bai and Anderson (2016) measure profitability as the net income from patient care services per adjusted discharge based on fiscal year 2013. Their study shows that 46% of hospitals are not profitable, and unprofitability of hospitals are more sensitive to not-for-profit hospitals and hospitals that treat a larger percentage of Medicare, Medicaid, and uninsured patients. Freidman, Sood, Engstrom and McKenzie (2004) also studied hospital profitability for inpatient care by payer and noted that Medicaid was the least profitable compared to Medicare, Private Insurance, and self-pay.

Additionally, since over half the states participated in the Medicaid expansion, the total number of Medicaid members grew, but the reimbursement to hospitals for patient care did not. "The largest public payers continue to underpay hospitals, data from the most recent American Hospital Association (AHA) Annual Survey of Hospitals revealed. Medicare and Medicaid reimbursement fell $76.8 billion short of the actual costs of treating beneficiaries in 2017. Medicare reimbursement was $53.9 billion short of actual hospital costs, while Medicaid underpaid hospitals by about $22.9 billion" (Lapoint, 2019). Medicaid pays between $0.85 to $0.87 on the dollar from 2010-2018 for all charges incurred at the hospital. With the growing number of Medicare patients (approximately 10,000 newly eligible people aging in per day) and the increased number of Medicaid patients and newly insured, low income, and exchange patients, hospitals are not seeing as many commercial patients in the ER or as inpatient admits (Deloitte Insights, 2018).

Many of the high cost charges were being generated by the lowest reimbursed part of the business (Medicaid). Therefore, some hospitals negotiate higher rates on commercial business, expecting the excess amounts to compensate for the low reimbursement for Medicaid Patients (Barkholz, 2016). Wagner (2015) research highlights how the Medicaid expansion led to higher prices and how hospital administrators thought they would have to charge patients with private/commercial insurance enough to cover their services and the deficit generated by Medicaid or Medicare reimbursement. There was a shifting from private insurance to Medicaid resulting in revenue losses holding patient mix constant. However, that shift does not support an increase in privately covered patients, noting cost shifting is not occurring in response to Medicaid Expansions. Instead, they reduce charges for privately insured patients, causing privately insured to benefit from the Medicaid expansions in terms of hospital charges. This is evidence that there must be other ways hospitals are addressing revenue losses caused by Medicaid Expansions.

Social Determinants of Health

There is a significant amount of prior research that shows a connection between an individual's socioeconomic status or certain social determinants of health and their health outcomes. As it relates to a person's income status, Lenhart (2017) research finds that higher wages result in lower overall mortality and lower income individuals have been more prone to death from their health issues. When care is free of charge or there is no out-of-pocket cost to the patient, individuals increase their number of doctor visits by 5-10% (Nilsson and Paul, 2018), thereby increasing their chances of mitigating potentially devastating health issues. There has been some difficulties in determining causation between socioeconomic status and health outcomes which resulted in some literature taking some different approaches to find causation. Allin and Stable (2012) research finds that effects of the socioeconomic status also could pass down to the children of the parents, causing them to suffer the same adverse health outcomes as their parents. Additionally, the upward mobility of the child can be beneficial to the parent, and that parents, with both high and low socioeconomic status, can benefit from having a child with a high socioeconomic status (Zimmer, Hanson, Smith, 2016).

Another SDOH is residential segregation which focuses on the geographic location of the person. People in poorer neighborhoods are documented to have significantly more ambulatory visits for ambulatory care sensitive conditions than people that live in more affluent neighborhoods (Roos, et al, 2005). Other studies have looked at the variation of health gaps that exist across more developed and richer countries and have shown that low socioeconomic statuses lead to poorer health versus poor health leading to low socioeconomic status in richer more developed countries (Lleras-Muney, 2018). This further supports the idea that where a person lives can have a negative effect on their health outcomes.

There are also studies that link a person's race/ethnicity and socioeconomic status to their health outcomes. There are studies that correlate "white privilege" to better health outcomes by looking at body mass index (BMI) and associating the greater BMI of people with darker complexions to lower socioeconomic statuses and poorer health (Carson, 2015). In some cases, a hospital's profitability would be affected if they took into consideration the sensitivities of racially and ethnically diverse individuals. For example, the Hospital Readmission Reduction program of the Centers of Medicare and Medicaid Services assess penalties for hospital readmissions and studies found that after adding race/ethnicity along with low socioeconomic status of individuals into the readmissions penalty calculation, most hospital would see significant decreases to their penalty payments (Martsolf, et al, 2016). This study opens the opportunity for other studies to look at sensitivities of race/ethnicity as it relates to risk adjustment for other areas.

There has been some progress with hospitals investing in social determinants of health, however it is not clear that there was a clear connection between that investment and their profitability. Horwitz et.al. (2020) discusses the "sizable" investments in social determinants of health by health systems, but also recognizes that those investments are not specific to community-based activities. Many of those investments are health related and does not go too far beyond that, despite the ACA regulations that required tax exempt hospitals to do community needs assessments.

My research will build on these findings and discuss how improving social determinants of health of individuals and can result in both better health outcomes and higher profitability for hospitals.

III. Data Sources

Primary Data Source

I use the 2014 Healthcare Cost and Utilization Project (HCUP) [4] National Inpatient Sample (NIS) which is sampled from the State Inpatient Database (SID) and accounts for all inpatient data submitted to and reported by HCUP as the primary source for the population I analyze. "The NIS is a database of hospital inpatient stays derived from billing data submitted by hospitals to statewide data organizations across the U.S. These inpatient data include clinical and resource use information typically available from discharge abstracts. Researchers and policy makers use the NIS to make national estimates of health care utilization, access, charges, quality, and outcomes. The NIS covers all patients, including individuals covered by Medicare, Medicaid, or private insurance, and the uninsured. For Medicare, the NIS includes Medicare Advantage patients, a population that is missing from Medicare claims data but that comprises as much as 20 percent of Medicare beneficiaries. The NIS' large sample size enables analyses of rare conditions, uncommon treatments, and special patient populations" (Introduction to The HCUP National Inpatient Sample, 2014, p. 4). The details of the NIS are normally available to the public through HCUP approximately 3 years in arrears. For example, the 2017 NIS Sample was just made available on September 1, 2020. Therefore, at the time I began this research, the 2014 NIS Dataset was the most complete version of data to use at

[4] Detailed information on The HCUP National Inpatient Sample (NIS) 2014 can be found at http://www.hcup-us.ahrq.gov

that time. The NIS was redesigned in 2012 to improve the national estimates. This dataset was the last version of the NIS that only included the ICD-9-CM diagnosis and procedure codes (in 2015 the ICD-10 CM diagnosis and procedure codes were introduced). Additionally, it included inpatient discharge data for the state of Maine, after not being included for the prior two years. The hospital service line (discussed later) was also added as a new data element in 2014.

This dataset includes 7,071,062 total observations of inpatient discharge data. My analysis looks at all observations but focus on select data elements as the base of my research. Unfortunately, all data elements were not provided for every observation, which resulted in some missing data and omitted data during the regression because of collinearity. However, the amount of missing or omitted data was not significant enough to materially impact my results (which will be discussed later).

The independent variables are the 29 comorbidities identified in the dataset. Comorbidities, as defined by Valderas, et.al (2009), “the presence of more than 1 distinct condition in an individual”. All the comorbidities are presented in the dataset as binary where 1 indicates that the comorbidity is present and 0 indicates the comorbidity is not present. These comorbidities included in Figure 5:

Figure 5

Comorbidity	Dataset Name
AIDS	CM_AIDS
ALCOHOL ABUSE	CM_ALCOHOL
DEFICIENCY ANEMIA	CM_ANEMDEF
RHEUMATOID ARTHRITIS	CM_ARTH
CHRONIC BLOOD LOSS ANEMICA	CM_BLDLOSS
CONGRESTIVE HEART FAILURE	CM_CHF
CHRONIC PULMONARY DISEASE	CM_CHRNLUNG
COAGULOPATHY	CM_COAG
DEPRESSION	CM_DEPRESS
DIABETES	CM_DM
DIABETES W/ CHRONIC COMPLICATIONS	CM_DMCX
DRUG ABUSE	CM_DRUG
HYPERTENSION	CM_HTN_C
HYPOTHYROIDISM	CM_HYPOTHY
LIVER DISEASE	CM_LIVER
LYMPHOMA	CM_LYMPH
FLUID & ELECTROLYTE DISORDERS	CM_LYTES
METASTATIC CANCER	CM_METS
OTHER NEUROLOGICAL DISORDERS	CM_NEURO
OBESITY	CM_OBESE
PARALYSIS	CM_PARA
PERIPHERAL VASCULAR DISDORDERS	CM_PERIVASC
PSYCHOSES	CM_PSYCH
PULMONARY CIRUCLATION DISORDERS	CM_PULMCIRC
RENAL FAILURE	CM_RENLFAIL
SOLID TUMOR WITHOUT METASTASIS	CM_TUMOR
PEPTIC ULCER DISEASE	CM_ULCER
VALVULAR DISEASE	CM_VALVE
WEIGHT LOSS	CM_WGHTLOSS

The control variables originally presented in the dataset were a mixture of continuous and categorical variables (except for the comorbidities). Length of Stay (LOS) represents the amount of days a patient stays in the hospital after being admitted. The LOS was added as a control variable because of its direct impact to hospital COST. According to the Organization of Economic Co-operation and Development (OECD), "The average length of stay in hospitals

(ALOS) is often used as an indicator of efficiency. All other things being equal, a shorter stay will reduce the cost per discharge and shift care from inpatient to less expensive post-acute settings" (OCED, 2020). The LOS was originally a continuous variable that ranges from 1 to 365 days. I reclassified the LOS to 7 binary variables (0-4 days, 5-9 days, 10-14 days, 15-19 days, 20-24 days, 25-29 days and 30 plus days) where 1 indicates the hospital stay falls within the variable's specified days and 0 indicates it does not fall within those days. I group the LOS into those specific categories since 99.1% of all inpatient stays happen in the first 30 days.

Hospital Control is another data element used as a control variable in the first regression. Hospital Control is defined as the type of entity that has ownership of the hospital. This data element was added as a control variable because research has shown that hospital ownership has a significant impact on hospital profitability. Based on prior empirical research, there appears to be significant differences in financial performance of for-profit (private) hospitals and not-for profit hospitals (Shen, et.al., 2007). In the data set, Hospital Control was originally presented as a categorical element where 1 indicated the hospital was owned by government or non-federal, 2 indicates private, non-profit ownership and 3 indicates private, investor-owned ownership. These 3 categories were reclassified to 3 separate binary variables for each Hospital Control type where 1 indicates ownership/control for the respective Hospital Control type and 0 represents no ownership/control.

Hospital Bed Size is also a data element used as a control variable in the first regression. I view the bed size of the hospital as its capacity to take on patients which could be revenue generating. However, smaller hospitals may not have the same opportunity as larger hospitals to reap benefits of profitable lines of business and are not able to spread inpatient cost over a large amount of hospital beds. Therefore, it is important to see the variation between the bed size of the hospital. In the data set, the hospital bed sizes varied across 4 regions (Northeast, Midwest, Southern and Western) and was further measured by Hospital Location (described later).[5] Therefore, what is considered small, medium and large in the Northeast Region may not be measured the same as it is in the Midwest region. Hospital Bed Size was originally presented as a categorical element where 1 indicated a small number of hospital beds, 2 indicated a medium number of hospital beds and 3 indicated a large amount of hospital bed. I reclassified these 3 categories of bed size into 3 different binary variables where 1 indicate the observation is that bed size (small, medium, or large) and 0 indicates it is not.

Payer is a data element used as a control variable in the first regression. Payer represents the primary expected payer of the patient's hospital bills. This can include a private insurance company, government insurance or the actual patient which may be responsible for the hospital bill if they do not have health insurance. The specific payer type can tell you a lot about the patient including

[5] Detailed breakdown of Small, Medium, Large bed sizes are available at https://www.hcup-us.ahrq.gov/db/vars/hosp_bedsize/nisnote.jsp

their socio-economic status, which is critical in analyzing how that affects hospital cost and health outcomes. In the data set, Payer was originally presented as a categorical element where 1 indicated the patient was covered by Medicare, 2 indicated the patient was covered by Medicaid, 3 indicated the patient was covered by a private insurance including HMO (normally coverage offered by an employer), 4 indicated the self-pay and the patient is responsible, 5 indicated no charge (unreimbursed Native Health), and 6 indicated the patient was covered by other types of insurances (i.e., Workers Compensation, CHAMPUS/VA, Indian Health Service, other government insurance). I reclassified these 6 categories of Payers into 6 different binary variables where 1 indicates the responsible party for the patient's hospital bill is that of the variable (i.e., Medicare, Medicaid, etc.) and 0 indicates it is not.

Lastly, I used the data element Service Line as a control variable for the first regression. I added Service Line because all reasons for hospitalizations are not monolithic and each reason has its own unique impact to overall hospital profitability. Service Line represents all discharges from the hospital and was originally presented in the dataset as a categorical element of hospitalization types where 1 indicated maternal/neonatal, 2 indicated mental health/substance abuse, 3 indicated injury, 4 indicated surgical and 5 indicated medical. I reclassified each category into its own binary variable where 1 indicated that the observation's service line was the specific type specified (i.e., maternal/neonatal, injury, surgical, etc.) and 0 indicated that it was not.

The second regression went further to explain whether there is any type of impact to hospital COST because of a patient's SDOH. There have been several studies as noted in the Literature Review section, that discussed the correlation between an individual's health outcomes and their socioeconomic circumstances. The impact of an individual's socioeconomic status on their health outcomes can be directly driven by an individual's personal decisions such as choosing to forgo medications or follow-up doctor appointments due to their low-income status and not having the available funds to cover out-of-pocket costs (i.e., copays, deductibles, etc.) (Nilsson and Paul, 2018). The impact on health outcomes can also be indirectly driven by circumstances outside of an individual's control such as the lack of access to grocery stores to obtain fresh nutritious food or living in a neighborhood with little to no access to healthcare providers (Lleras-Muney, 2018). I selected comorbidities to represent an individual's health outcome because comorbidities are a combination of multiple related diseases and diagnoses of an individual. SDOH are combination of several socioeconomic factors that could also be related to a person's health outcome based on prior research.

This regression was more complex as I needed to look at the impact of the social determinants on all 29 comorbidities separately as dependent variables and with each social determinant as independent variables separately as well, while controlling for Race, Household Income, Hospital Location and other comorbidities that were not being analyzed as the dependent variable.

I had to look beyond the dataset elements to explore this assumption because SDOH were not captured at the point of admission for an inpatient hospital stay and therefore, the information is not reported in the NIS as of 2014. In 2019, CMS introduced some ICD-10-CM diagnosis codes that could be used to identify certain types of SDOH such as problems related to education, problems related to employment and unemployment, occupational exposure to risk factors, problems relates to physical environment, problems related to housing and economic circumstances, problems related to social environment and problems related to psychosocial circumstances (James, 2019). Unfortunately, this information was not collected in 2014 and is not consistently captured now. Therefore, I had to create the variables using external information obtained from various sources. My focus is on a patient's living environment, food insecurities, and issues surrounding employment. I obtained information on Violent Crime to analyze the living environment, gathered information on distribution of Supplemental Nutrition Assistance (SNAP) to analyze food insecurities and the unemployment rates to analyze issues around employment. All the amounts used to analyze the effects of the SDOH are grouped into the nine US Census divisions of the hospital as referenced in the HCUP 2014 NIS dataset. Each division includes the specific states the US Census assigned based on geographical area. I group the SDOH by hospital division because trends and practice patterns vary across the United States and the division is the most detailed level to stratify the inpatient data I use for this research. Therefore, the SDOH amounts could only be 1 of 9 values as shown in Appendix 1.

Violent Crime Rate was obtained from the FBI Crime in the United States by Region, Geographic Division, and State 2013-2014 Table 4. Per this source data, violent crime is defined as murder and nonnegligent manslaughter, rape, robbery, and aggravated assault. I present the value of violent crime as the average number of incidents per 100,000 people at the Hospital Division level (as defined by the NIS dataset) as a categorical variable. I use an average number of incidents because the information included on the FBI report was for the time from July 2013 through June 2014.

SNAP values were obtained from the USDA Food and Nutrition Services Supplemental Nutrition Assistance Program State Activity Report Fiscal Year 2014. I use the average monthly benefit per household from Table 2 of the report. The average amounts were presented in the report at the state level and I reclassify each state into the average monthly benefit per household at the Hospital Division level (as defined by the NIS dataset) and present as a categorical variable.

Unemployment rates were obtained from the Kaiser Family Foundation State Health Facts as of September 2014. The unemployment rates are based on the overall population of individuals that are 16 years or older and are considered employable and actively looking for work. The unemployment rates are presented in the report at the state level and I reclassify each state into the Hospital Division level (as defined by the NIS dataset) and presented it as a categorical variable.

Race, Gender, Household Income and Hospital Location were all data elements available in the NIS dataset. I selected these data elements to be control variables because they help identify the patient's socioeconomic status and environment.

Race represents the race of the patient at the time of hospitalization. Race was originally presented as a categorical variable in the NIS dataset, but was only available for about 94% of the observations (approximately 6% of the Race data was missing). The race categories were classified as 1 for white, 2 for black, 3 for Hispanic, 4 for Asian or Pacific Islander, 5 for Native American and 6 for other. I reclassify these categories into separate binary variables where 1 indicated the patient was of that race identified by the variable (i.e., black, white, etc.) and 0 indicated that they were not. All the missing variables defaulted to the Other race data element.

Gender represents whether the patient is a male or a female. Gender was already presented as a binary variable where 1 indicates female and 0 indicates male.

Household Income represents the median household income quartiles based on the patients' zip code. Household income was originally presented as a categorical data elements where 1 indicated households with incomes of $1 to $38,999, 2 indicated households with incomes of $39,000 to $47,999, 3 indicated households with incomes of $48,000 to $62,999 and 4 indicated households with incomes of $63,000 or more. I reclassify each household income category into separate binary variables where 1 indicated the patient's household income identified by the variable (i.e., $1 to $38,999, $63,000, etc.) and 0 indicates that the patient's household income was not that specific category.

Hospital Location represents the type of location (urban or rural) and the teaching status of the hospital that the patient was admitted to. I chose hospital location versus the location of the patient's residence because I believe it better represents how the hospital is impacted by treating patients affected by the SDOH. The Hospital Location was originally presented as a categorical data element where 1 indicated rural, 2 indicated urban/non-teaching and 3 indicated urban/teaching. As with the other control variables, I reclassify each hospital location category into its own separate binary variable where 1 indicate the patient's hospital is in that specific location identified by the variable (i.e., rural, urban/teaching, etc.) and 0 indicates that the hospital is not in that specified location.

IV. Data Method

Econometric Model

My analysis has two parts, the first part looks at the influence of comorbidities on hospital cost while controlling for length of stay, hospital control, hospital bed-size, payer (insurance) type, and service line. The second part of the analysis explores if and to what extent SDOH cause those comorbidities and as a result, attributed to increases in hospital costs. The first part analysis consists of one dependent variable (COST). The calculate variable COST is a formula based on total billed charges included in data set deflated by average cost to charge ratio[6]. My primary assumption is that SDOH (SDOH) contributes to comorbidities (CM) which causes hospital inpatient cost (COST) to increase and profitability to erode. So, my goal is to determine if there are cost savings to the hospital if the SDOH improved by one standard deviation. To further explore this assumption, I perform two regression analyses, one linear regression and one instrumental variable regression and calculate potential savings based on improving the SDOH by one standard deviation. The first regression determines to what extent CMs affect COST while controlling for Length of Stay (LOSDAYS_*), Hospital Control (H_CONTRL_*), Hospital Bed Size (HOSP_BEDSIZE_*), Payer (PAY1_*), Services Line (SERVICELINE_*) and all comorbidities (CM_*). The linear regression's construction is as follows:

$$\mathbf{Y= \beta_0 + \beta_1X_{1i} + \beta_2X_{2i} + \beta_3X_{3i} + \ldots\ldots\ \beta_nX_{ni} + u}$$

Where:

$\mathbf{Y}$ = COST

$\mathbf{X_1 - X_7}$ = Length of Stay variables

$\mathbf{X_8 - X_{13}}$= Payer variables

$\mathbf{X_{14} - X_{16}}$= Hospital Control variables

$\mathbf{X_{17} - X_{19}}$= Hospital Bed Size variables

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[6] Cost to Charge Ratio = total Billed charges/total allowable cost

$\mathbf{X_{20}}$ - $\mathbf{X_{24}}$= Service Line variables

$\mathbf{X_{20}}$ - $\mathbf{X_{48}}$= All the comorbidities variables

$\mathbf{u}$ = error term

In the second regression, I explore the factors behind the comorbidities because per the assumption above, I believe at some level, SDOH causes an individual's comorbidities along with other control variables. I regress the three SDOH variables (i.e., Violent Crime, SNAP, and Unemployment) and all 29 comorbidities and controlled for Race, Gender, Income Level, and Hospital Location. Since the comorbidities are binary and are also the dependent variables, the regression would be a probit regression.

To account for the potential endogeneity problem, I use an Instrumental Variable (IV) approach. To further exploit the SDOH, I needed to identify a unique variable that would help me isolate the piece of the SDOH that is uncorrelated with the error term but is correlated with SDOH. To do this, I would need to do an instrumental variables regression (IV). I selected Political Affiliation of the region of all patients in the data set as the IV instrument because it is correlated with the SDOH directly through legislation that determines socioeconomic outcomes as a result of laws passed or indirectly through legislation or policy that are heavily influenced by the dominant Political Affiliation of the patient's region. Political Affiliation fulfills all OLS assumptions including the instrumental variable (IV) assumption of instrument relevance and instrument exogeneity because it correlates to SDOH, but it is not driven by the individual's comorbidity.

Political Affiliation (i.e., Democrat, Republican) serves as a proxy for governmental policies reflected in the geographic division of which the SDOH are identified. Often the policies that are in place are swayed by the position of the political affiliation that is dominant in that area. For example, Democrat leaning areas may favor more government funding which would result in having a larger amount of average SNAP distributions per household. Also, Republican leaning areas may favor policies that discourage government spending and executive overreach which a lot of times includes financial assistance that may help disenfranchised communities at large and could result in higher levels of unemployment. Democrats and Republicans have varying views on crime as well, ranging from demanding harsher penalties for offenders (Republicans) to being in favor of police reform because of over-policing (Democrats). SNAP's distribution amounts are directly determined by governmental policies since the household allocation amounts and requirements around how those amounts are distributed, are voted on and decided by a specific state's elected officials. Unemployment is indirectly caused by government policies but are heavily impacted by government policies such as monetary policy, fiscal policy, outsourcing, etc. Violent Crime is partially driven by government policy and partially by sociological circumstances.

Political Affiliation is determined by the classification of the legislative composition in each state in 2014 per the National Conference of State Legislatures Partisan Composition of State Legislatures in 2014. States were identified as Democrat, Republican or Split and were given values of 1, 2 or 3, respectively. All states were reclassified based on the hospital divisions per the NIS dataset. I took the legislative composition value (1, 2 or 3) by state and calculate the average legislative composition value by division. To determine the Political Affiliation at the division level, I create a binary variable where any division average that is less than 2 is assigned 1 (Democrat) and averages over 2 are assigned 0 (Republican).

Political Affiliation is correlated with the SDOH variables and is not correlated with the error term as evidenced by the Wald test of exogeneity. As a result, the second regression should be an IVProbit regression as follows:

$$\mathbf{Y = \beta_0 + \beta_1 X_i + \beta_2 W_{1i} + \beta_2 W_{2i} + \beta_3 W_{3i} + \ldots\ldots.\ \beta_n W_{ni} + u}$$ [7]

Where:

Y = Comorbidity (for each selected CM per regression there are separate regressions where the individual CM is the dependent variable)

[7] The TSLS estimator in the IVProbit regression is done in 2 stages. In the first stage I regress X on instrumental Variable Z (Political Affiliation). In the second stage I regress Y from the IVProvbit Regression TSLS on the predicted values and the included exogenous variables (W) using OLS including the intercept. Please note, in the software used to do regressions, these steps are performed simultaneously.

X_i = SDOH – Endogenous Variable (using instrument Z such that $X_i = \pi_0 + \pi Z_{1i} + \pi W_{1i} + \pi W_{1i} + \pi W_{1i} + \pi W_{1i} + \pi W_{1i} + v_i$, where **Z = Political Affiliation**

W_{1i} – W_{6i} = Race variables

W_{7i} = Gender variables

W_{8i} – W_{11i} = Household Income variables

W_{12i} - W_{14i} = Hospital Location variables

W_{15i} – W_{42i} = All Other 28 CMs (not including the CM selected as the dependent variable.

u = error term

The second regression requires each CM to be a dependent variable and be regressed against each SDOH in separate IVProbit regressions.

Cost Savings Results

Next, I determine to what extent overall hospital COST could be reduced if the SDOH improved by one standard deviation for Violent Crime, Unemployment and SNAP. Improving Violent Crime by one standard deviation means that the average number of incidents of violent crime per 100,000 people will decrease resulting in less violent crime. Improving Unemployment by one standard deviation would mean that average unemployment rate would decrease. For the comorbidities that cause COST to increase and that are caused by Violent Crime or Unemployment (both represented by positive coefficients), the improvement by one standard deviation (also positive) will result in cost savings. Improving SNAP by one standard deviation represent an increase in the average amount of SNAP funds per household which would ultimately decrease the level of food insecurity. To reflect the effect on cost savings, I switch the sign of the standard deviation when calculating the COST savings because an improvement by one standard deviation has an inverse effect on the SNAP distribution. For the comorbidities that both caused COST to increase and that are caused by circumstances around SNAP (i.e., food insecurity), the improvement by one standard deviation will determine the cost savings.

I calculate the standard deviations for each SDOH variable. To do this I use the average number of Violent Crime incidents, the average distribution per household for SNAP and the average Unemployment rate by Hospital Division[8] and calculate the standard deviation for each SDOH across all nine divisions for the full dataset. Next, I take the coefficient for each SDOH variable from each CM IV Probit regression which represents the likelihood or probability that an individual with that SDOH (i.e., that lives in an area with Violent Crime) will also suffer from the specific CM (dependent variable) and multiply it by the one standard deviation for the SDOH variable. This tells me the portion of the standard deviation improvement directly tied to the CM that is caused by the

[8] The dataset only went as granular as the Division which resulted in the Standard Deviation being artificially constrained as the SDOH amounts could only be one of 9 numbers.

SDOH. Next, I use summary statistics to identify the total number of individuals with each CM by tabulating each CM from the full dataset and multiplying it by the portion of the standard deviation improvement directly tied to the CM. This results in the total number of people with the CM that is caused by the SDOH, of which an improvement by one standard deviation would affect. Lastly, I multiply the total number of people affected by the SDOH by the CM coefficient from the first regression which shows the CM's effect on COST, to determine potential dollar savings. This full calculation is outlined below in Table 1:

Table 1

	1st Stage Cost Regression			2nd Stage Regression - Instrumental Variables					
Comorbidity	Comorbidity Coeffient	Total # of people with CM (full Dataset)	Pvalue P>|t|	Violent Crime Standard Deviation	IVProbit - Crime Coefficient	Pvalue P>|t|	Total improvement directly tied to this CM	Total # of People with CM associated with Potential Savings	High Level Savings at Comorbidity Level
	a	b	95% C.	c	d	95% C.	e = c*d	f = e*b	g = a*f

V. Results from Empirical Research

COST Regression

I show there is an impact on hospital COST caused by the comorbidities while holding Length of Stay, Payer, Hospital Control, Hospital Bed Size and Service Line constant. There are favorable and unfavorable effects on COST savings from the comorbidities. The coefficient of the comorbidities that are positive indicates an unfavorable effect on COST and represented the incremental COST increase that results from a person having that specific comorbidity. Figure 6 includes the coefficients of the Comorbidity with adverse effect on COST.

Figure 6:

Comorbidity	CM Coeff
CM_ALCOHOL	188.25
CM_BLDLOSS	1,255.49
CM_CHF	127.07
CM_CHRNLUNG	364.48
CM_COAG	5,385.73
CM_DM	103.94
CM_DRUG	203.86
CM_LIVER	496.63
CM_LYMPH	923.55
CM_LYTES	2,216.55
CM_NEURO	428.35
CM_OBESE	466.71
CM_PARA	207.29
CM_PERIVASC	98.37
CM_PULMCIRC	2,236.82
CM_RENLFAIL	426.56
CM_ULCER	916.04
CM_WGHTLOSS	1,677.10

All comorbidity coefficients have p-values at or below 0.01. There are also comorbidities that do not individually cause COST to increase while holding all other variables constant. Figure 7 includes these comorbidities and their coefficients.

Figure 7:

Comorbidity	CM Coeff
CM_ANEMDEF	-342.881
CM_DEPRESS	-449.842
CM_DMCX	-654.92
CM_HTN_C	-46.3697
CM_HYPOTHY	-219.577
CM_METS	-347.715
CM_PSYCH	-665.955
CM_TUMOR	-313.949

These comorbidities are also statistically significant with p-value less than 0.01. It is important to note these additional comorbidities also plays a role in overall hospital COST impact since people with comorbidities must have at least two. This means that the COST of one comorbidity may be offset by the other or combined with another comorbidity.

The results of this first regressions shows that comorbidities are a contributing factor in causing hospital COST to increase and negatively impacting hospital profitability.

Instrumental Variable Probit Regression and Savings Calculation

The second regression is the instrumental variables probit (IVPROBIT). I look to see if the SDOH (Violent Crime, SNAP, and Unemployment) causes the comorbidities that have the statistically significant adverse effect on COST. I note that the three SDOH variables have a statistically significant impact on the following comorbidities with p-value less than 0.05: Alcohol, Congestive Heart Failure, Chronic Pulmonary disease, Coagulopathy, Depression, Diabetes without complications, Diabetes with complications, Hypertension, Hypothyroidism, Liver Disease, Lymphoma, Fluid and Electrolyte Disorders, Metastatic Cancer, Neurological Disorders, Obesity, Paralysis, Peripheral Vascular Disorder, Psychoses, Pulmonary Circulation, Renal Failure, Solid Tumor with Metastasis, Peptic Ulcer Disease and Weight Loss.

To determine the estimated cost savings, calculated based on improving SDOH by one standard deviation, I split the cost savings into two categories. The first category is direct COST savings which includes the calculated savings based on the specific comorbidities that has both a positive SDOH coefficient and a positive comorbidity coefficient. Since both coefficients go in the same positive direction, the impact of the SDOH on the comorbidity flows through the comorbidity to COST, thus reflecting the COST savings attributed specifically to those comorbidities and SDOH variables. The second category is Total Savings which includes the sum of all calculated cost savings for all statistically significant comorbidities. As stated above, comorbidities are not mutually exclusive, therefore, it is important to include the net sum of all statistically significant comorbidities which would include some that do not have the same positive directional effect on COST. I present the calculated cost savings in dollars and as a percentage of total cost ($75,469,829,306.87) from the dataset. This enables me to highlight the full range of COST Savings that can be realized if the SDOH is improved by one standard deviation of 79.01795, 24.90658, and 0.0082279 for Violent Crime, SNAP, and Unemployment, respectively.

For Violent Crime (Appendix 2), the comorbidities that have positive comorbidity and SDOH coefficients are Coagulopathy, Diabetes without complication, Electrolyte Disorder and Weight Loss. Based on the total number of people with these comorbidities and improving violent crime by one standard deviation, I calculate the COST savings full range to be $119,514,400 through $160,967,652, where the $161M is the direct COST savings related to the four comorbidities that have positive comorbidity and SDOH coefficients and the $119.5M is the total COST savings. Since the full range cost savings amounts are all positive, this indicates that if violent crime improves by one standard deviation, total hospital cost will decrease between 0.16% (total) and 0.21% (direct) and will result in a favorable impact on hospital profitability.

For SNAP (Appendix 3), there are more comorbidities that have positive comorbidity and SDOH coefficients. These comorbidities are Alcohol, Congestive Heart Failure, Chronic Pulmonary Disease, Drugs Abuse, Liver Disease, Lymphoma, Neurological Disorders, Obesity, Paralysis, Peripheral Vascular Disorder, Pulmonary Circulation, Renal Failure, and Peptic Ulcer Disease. Based on total number of people with these comorbidities and improving SNAP by one standard deviation, I calculate the COST savings full range to be -$203,904,405 through $368,063,384 where the -$204M is the direct COST savings related to the thirteen comorbidities that have positive comorbidity and SDOH coefficients and the $368M is the total COST savings. The directly impacted comorbidities do not seem to result in any COST savings, however, the net effect of the range seems to reflect favorable COST savings. Therefore I determine that since the full range cost savings amounts are all positive, this indicates that if SNAP distributions improve by one standard deviation, total hospital cost will decrease up to 0.5% (total) and will result in a favorable impact on hospital profitability, but only if all comorbidities are taken into account.[9]

For Unemployment (Appendix 4), the comorbidities that have positive comorbidity and SDOH coefficients are the same as the ones identified for Violent Crime (Coagulopathy, Diabetes without complication, Electrolyte Disorder and Weight Loss). Based on the total number of people with these comorbidities and improving unemployment by one standard deviation, I calculate the potential COST savings full range to be $930,589,828 through $1,252,670,559, where the $1.3B is the direct COST savings related to the four comorbidities that have positive comorbidity and SDOH coefficients and the $930M is the total COST savings. As with violent crime, since the full range cost savings amounts are all positive, this indicates that if unemployment improves by one standard

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[9] It is important to note that calculation for increasing by one standard deviation is adding to the average SNAP distribution per household so the calculation for standard deviation is a negative amount.

deviation, total hospital cost will decrease between 1.2% (total) and 1.7% (direct) and will result in a favorable impact on hospital profitability.

Wald Test of Exogeneity

To determine if the SDOH variables cause hospital COST to increase through the comorbidities, I run an instrumental variables regression (called IVPROBIT in Stata). I suspect the SDOH variables are correlated with the error term and I use Political Affiliation as an instrument to isolate the piece of the SDOH variables that are uncorrelated with the error term. The Wald Test of Exogeneity determines whether the instrumented variables are exogenous to the error term. The goal of this test is to tell us if it is appropriate to use an instrumental variables regression over a regular probit regression. The null hypothesis for the Wald Test of Exogeneity is that the instrumented variable (i.e., Violent Crime, SNAP or Unemployment) is not endogenous, therefore there would be no need to run an instrumental variables regression using Political Affiliation as the instrument. If I reject the null hypothesis, that indicates that the instrumented variables are endogenous to the error term and the use of the Political Affiliation instrument was appropriate, therefore the IVProbit regression was appropriate.

Based on the instrumental variables regressions for Violent Crime, SNAP and Unemployment that have statistically significant impact on the comorbidities that are identified as having direct COST savings, I am able to reject the null hypothesis of no endogeneity for all Violent Crime and

Unemployment regressions for the 4 effected comorbidities (Coagulopathy, Diabetes without Complication, Electrolyte Disorder and Weight Loss). I also reject the null hypothesis of no endogeneity for SNAP for all of the effected comorbidities (Alcohol, Congestive Heart Failure, Chronic Pulmonary Disease, Drugs Abuse, Liver Disease, Lymphoma, Neurological Disorders, Obesity, Paralysis, Peripheral Vascular Disorder, Pulmonary Circulation, and Renal Failure) except for Peptic Ulcer Disease. Since the chi2 value (p-value) for Peptic Ulcer Disease is greater than 0.05, this suggests that SNAP is not correlated with the error term and that a normal probit regression should be used. I run a probit regression with Peptic Ulcer disease as the dependent variable and SNAP being the independent variable along with the same control variables that are used in the IVProbit regression but do not include Political Affiliation. The original estimated COST savings under the instrumental variable's regression was -$122,652. The total COST savings after removing Political Affiliation as an instrument and running a regular probit regression, was -$86,651 which is an increase of about 29%. Therefore, I use the coefficient of SNAP for the probit regression of Peptic Ulcer disease to ensure my COST savings estimates are more accurate, however, it is important to note that the overall impact of the SNAP direct effect on COST savings is only 0.02%.

Micro Analysis

As noted above, my results indicate that there is evidence that addressing SDOH by improving Violent Crime, Unemployment and SNAP by one standard deviation will result in hospital cost savings and thereby, increase hospital profitability. However, this analysis is at the macro level and may not specifically address the intricacies that exist across all diagnoses within a specific comorbidity. Some specific diagnoses may be more (or less) sensitive to SDOH than others. With that understanding I repeat my analysis done on the full population of this dataset, and run a micro analysis on a specific diagnosis related group (DRG) to determine if the correlation and causation of SDOH to hospital COST is still present.

I select an orthopedic procedure, DRG 470 – Major Joint Replacement or Reattachment of Lower Extremity Without Major Complication or Comorbidity. This DRG is most synonymous with knee replacements or hip fractures of patients that are not actively treating any complications or comorbidities at the time of surgery. Some patients may have a history of comorbidities; however, the presence of those comorbidities would not influence the surgical procedure. If the patient is currently treating any chronic conditions or comorbidities with medication at the time of surgery, DRG 469 – Major Joint Replacement or Reattachment of Lower Extremity with Major Complication or Comorbidity, should be used. I chose DRG 470 because the procedure is basic enough that anybody could receive it regardless of patient's demographic or socioeconomic status. It is a standard procedure that is most often performed very similarly regardless of the patient. The goal of my micro analysis is to determine if there is a correlation and causal relationship between SDOH and comorbidities and if there are COST savings being driven by a one standard deviation improvement in SDOH that have nothing to do with the procedure mix. I calculate the COST savings in the micro analysis the exact same way as the macro analysis, using the total cost for the DRG 470 dataset which is $3,304,396,448.41.

Appendices 5, 6 and 7 details the results of the regression analysis for DRG 470. The total number of observations in the DRG 470 subset data is 209,368. I apply the same methodology that was applied in the larger dataset noted in Appendices 2, 3 and 4 (including the same standard deviations). Violent Crime (Appendix 5) appears to directly impact Congestive Heart Failure, Diabetes with no complications, Fluid and Electrolyte Disorders and Weight Loss. If Violent Crime improves by one standard deviation, the full range of hospital COST savings are -$28,463,926 (-0.86% of total cost) to $1,058,154 (0.03% of total cost) where the $1.06M is the direct COST savings related to the 4 directly impacted comorbidities and the -$28.5M is the total COST savings. The net effect of these COST savings is negative which indicates that decreasing Violent Crime will not result in an increase in hospital cost savings and will not have a favorable effect on hospital profitability.

SNAP (Appendix 6) has a direct impact on eight comorbidities (Alcohol Abuse, Chronic Pulmonary Disease, Drug Abuse, Lymphoma, Obesity, Peripheral Vascular Disorders, Pulmonary Circulation and Renal Failure). The effect of SNAP on hospital COST savings mirrors what I show from the larger dataset. If SNAP is improved by one standard deviation, the full range of cost savings are -$11,886,339 (-0.36% of total cost) to -$5,667,695 (-0.17% of total cost) where the -$5.67M is the direct COST associated with the eight comorbidities and the -$11.88M is the total COST savings. The net effect of these COST savings is negative which indicates that an improvement in SNAP will not result in an increase in hospital cost savings and will not have a favorable effect on hospital profitability.

Lastly, DRG 470 Unemployment (Appendix 7) directly impacts five comorbidities (Congestive Heart Failure, Diabetes with no complications, Fluid and Electrolytes Disorder, Other Neurological Disorders, and Weight Loss). As with SNAP, Unemployment's effect on hospital COST savings mirrors the results found in the larger main analysis above. If Unemployment improves by one standard deviation, the full range of hospital COST savings are -$29,124,577 (-0.88% of total cost) to $7,130,937 (0.22%) where the $7.1M is the direct COST savings related to the five directly impacted comorbidities and the -$29.1M is the total COST savings. The net effect of these COST savings is negative which indicates that an improvement in Unemployment will not result in an increase in hospital cost savings and will not have a favorable effect on hospital profitability.

Although the results from the micro analysis does not support the overall results of the main analysis, it does not invalidate the overall conclusion that improving SDOH by one standard deviation will result in hospital cost savings. I used DRG 470 which is used when there are no major complications or comorbidities present at the time of surgery, therefore, I expected the aggregate results from the micro analysis to differ from the main analysis because the existence of the comorbidities are not as sensitive to how this procedure is performed or how much it costs in comparison to DRG 469 which includes major complications and comorbidities at the time to surgery. However, there still seems to be a correlation and causal relationship between directly impacted comorbidities and the SDOH resulting in COST savings of 0.03% for Violent Crime and 0.22% for Unemployment when improving SDOH by one standard.

VI. Future Research

This paper looks at the impact of Violent Crime, SNAP distributions and Unemployment on health outcomes and proved that an individual's exposure to those social determinants not only causes less than favorable health outcomes, but also attributes to higher hospital costs and improving those social determinants will result in cost savings to the hospital. However, these results in this paper should be cautiously considered given the limitations of available information from the NIS dataset as well as specific socioeconomic information that could have been used to provide a more detailed analysis of improvements in profitability and health outcomes. There is so much information included in the NIS dataset, the variation of additional analyses on this topic are widespread. Therefore, I have narrowed it down to a couple of areas that I feel would provide a richer analysis of the impact of health outcomes and hospital profitability because of improving SDOH.

This analysis has some constraints that prevent me from being able to analyze the information at a more granular level. The NIS dataset does not break out inpatient discharge data at the state level. The most detailed breakdown based on geographical information in the NIS dataset is at the Hospital Division level. Having the hospital inpatient discharge information at the state level and further, at the zip code level, would provide a clearer picture of how impactful the area specific SDOH is on an individual's health outcome. Socioeconomic factors vary significantly from state to state and city to city, even when those cities and states have dominant political affiliations in common. Additionally, the standard deviations at the zip code level and state level may vary from the Hospital Division level used in this paper. Therefore, to really understand the impact of potential cost savings resulting from improving SDOH by one standard deviation, you would need to know the more granular standard deviation.

There could also be some additional research specifically around Safety Net Hospitals. Safety Net Hospitals are essential hospitals that provide healthcare to primarily uninsured, underinsured, and low-income individuals and those covered by Medicaid. Given the population these hospitals serve, they are most at risk of skyrocketing costs as they see some of the sickest and poorest patients. As previous research has shown, a person's low-income status has an unfavorable effect on their health outcomes. As a result, the Safety Net Hospitals would significantly benefit from cost savings derived from improving the SDOH of the population they serve. All three SDOH indicators used in this paper would be relevant to use as a basis of analysis since low-income, uninsured individuals are likely to live in areas with higher crimes rates, food insecurity and higher possibility of being unemployed. Safety Net Hospitals' primary payer is Medicaid, which pays close to $0.85-$0.87 on the dollar, and the Disproportionate Share Hospital Payments[10] received from the government that is used to offset the cost of caring for low-income patients was recently cut and could mean a $44 billion reduction over the next 10 years, so improving the SDOH for the population they serve could significantly impact their profitability (Khullar et.al., 2018).

My regression analysis, though informative, is really the first step as it relates to what could be done to explore opportunities for hospitals to obtain cost saving by improving SDOH. The cost regression used the comorbidity's coefficients as the base for calculating cost savings. As mentioned earlier, comorbidities are present in an individual if they are deemed to have a comorbidity. Therefore, it would be helpful to interact several comorbidities to see if it yields a larger comorbidity coefficient. This would identify the combination of comorbidities that are driving the cost savings. I tested this theory by looking at Diabetes with chronic complications (Diabetes) and Hypertension before and after interaction. When I ran the first cost regression, the Diabetes coefficient was $103.94, and Hypertension's coefficient was -$46.37. Violent Crime was shown to cause Diabetes in some respects and Diabetes attributed to higher cost evidenced by both regression's coefficients

[10] More information on the Disproportionate Share Hospital Payment cuts can be found at https://www.modernhealthcare.com/payment/cms-finalizes-rule-cuts-medicaid-dsh-payments and https://www.medicaid.gov/medicaid/financial-management/medicaid-disproportionate-share-hospital-dsh-payments/index.html

having the same positive directional impact, so improving Violent Crime would yield cost savings by the amount of impact Violent Crime had on Diabetes. On the other hand, Hypertension's coefficient was -$46.37, which means that Hypertension alone is not a contributing factor in higher cost, even though Violent Crime has an impact on Hypertension. However, when I interact both Diabetes and Hypertension together, that coefficient was $70.25, which tells me that someone with both Diabetes and Hypertension as comorbidities attributes to higher healthcare cost, holding all other control variables constant. So, improving Violent Crime by one standard deviation would improve health outcomes of people with Diabetes and Hypertension, controlling for all other independent variables. I would also recommend interacting some comorbidities against some of the other control variables in the IV analysis such as Race and Household Income Level. As evidenced in prior research, certain minority populations (people of color) are more susceptible to some comorbidities based on their genetic makeup, or the likelihood that they may live in areas that are more impacted by socioeconomic factors. Also, a patient's income level could have a significant impact on their health outcomes because people are forced to have to choose between preventive care to keep from being chronically ill in the future and their livelihood now. Improving SDOH in these cases could possibly have a significant impact on health outcomes and in turn result in cost savings.

Another direction for future research is to rerun the analysis, taking into consideration, all SDOH assessed in this paper and additional SDOH not previously discussed in this paper including residential segregation, lack of education/literacy, and early childhood development. There is a possibility that further analysis could identify additional cost savings when compared to all the variables originally analyzed. There may also be more significant cost savings with other SDOH, that may be easier to address for a hospital or health system than the ones I analyzed in this paper. I also think it would be interesting to see the impact of how all SDOH combined would impact health outcomes. This would be done by adding instrumental variables in addition to Political Affiliation (IV regressions require the same number of instrumental variables as endogenous variables). By combining multiple SDOH together in one regression, we could start to piece together what an actual economic policy would look like related to improving these SDOH and addressing skyrocketing healthcare cost.

VII. Discussions on Processes and Policy Implications

Next, I address specific recommendations to improve these SDOH to yield the cost savings. It is important to note that these process and policy recommendations are costly, and their cost needs to be considered together with the cost savings. Unfortunately, we know that it will take more than the hospitals to invoke the type of improvements needed socioeconomically to see the improved health outcomes and increased profitability. However, given the information provided in this paper, hospitals can play a significant role in decreasing hospital cost associated with SDOH directly and indirectly.

Direct Efforts

Studies have shown that hospitals and health systems are starting to make financial investments in SDOH but the financial weight of those investments appear to be subpar considering how many hospitals are in the US and how impactful SDOH can be on their bottom line. There are some good examples of health systems that are making a deliberate effort to combat SDOH such as Kaiser Permanente which has invested $200 million to combat homelessness in Oakland, CA through their Thriving Communities Fund (Johnson, 2018). Unfortunately, this level of commitment is not quite widespread as it should be, and it may be because health systems have not been able to specifically tie return on investments (ROI) to the financial investments geared around improving SDOH. Making deliberate financial investments shows that the health system is dedicated to the cause of addressing SDOH of their patient population. According to Horwitz et al., (2020) health systems have publicly committed to investing in SDOH totaling close to $2.5 billion in the past two years. However, their community benefit through subsidized and uncompensated care (i.e., writing off claims), totaled approximately $60 billion, with only about 5 percent or less as direct financial investments in activities that are not specifically health related. From a financial perspective, it is easier to directly track the ROI from making deliberate financial investments as opposed to simply writing off unpaid claims or having it covered by charity care.

Another direct way to improve efforts around SDOH is for the health system to be more pro-active about screening patients when they are being admitted to the emergency room or for an inpatient stay by utilizing the new

SDOH diagnosis codes. Indeed, data collection can be instrumental in identifying patterns upon admission by directly identifying the socioeconomic cause, enabling hospitals the opportunity to take swift action in mitigating unnecessary subsequent visits that could result in increased cost. This would require providing additional training to front-line workers to be sensitive and aware of what to look for, what to ask, and how to handle these types of situations. Health systems can also ramp up their community-health worker resources. According to the American Public Health Association, Community Health Worker (CHW) is defined as, "a frontline public health worker who is a trusted member of and/or has an unusually close understanding of the community served. This trusting relationship enables the worker to serve as a liaison/link/intermediary between health/social services and the community to facilitate access to services and improve the quality and cultural competence of service delivery" (APHA, n.d.). Hiring people whose primary job's responsibility is to address SDOH of the patient is key to early high cost mitigation and improved health outcomes. CHWs can also work in collaboration with the provider (i.e., doctors) to help identify patients that may be more susceptible to SDOH. Often time, providers only come in at the highest cost point which is when the patient has been admitted to the emergency room or for an inpatient stay. Providers collaborating with the CHW can help mitigate overuse of inpatient services by identify issues that may be causing some of the acute reasons for admission.

Indirect Efforts

Cross-functional collaboration is a must for health systems to really reap the cost savings derived from improving SDOH. In addition to all the direct efforts noted above, health systems will need to look beyond their walls for assistance to combat these SDOH that are driving up cost and causing less than favorable health outcomes. One way to do this is to establish and improve relationships with community organizations with a specific focus on SDOH. This can be done by financially supporting some of those organizations' initiatives or collaborating with the organizations on those initiatives. An example would be ProMedica, an Ohio based health system that co-founded the Root Cause Coalition, a non-for-profit collaborative of health systems, health insurance companies, and community organizations geared around addressing causes of health inequity (Johnson, 2018, p.8). These types of investments allow dual benefits as it helps solidify the health system's position on moral and social responsibility to the community they serve, and it will ultimately improve their profitability as discussed in this paper.

Health systems should also ensure that their interest around SDOH are legislatively represented. In addition to securing lobbyist to address restrictions around healthcare reimbursement rates from government and commercial insurance payers, they should also ensure their interest is represented in other areas that may not directly affect healthcare economic policy but directly affects socioeconomic factors. This may include supporting candidates with platforms geared around improving the SDOH that are most impactful to the communities served by the health system. This could be a controversial suggestion especially in today's climate; however, this paper empirically proves that political affiliation is a driver for the elasticity of hospital cost savings because of improved SDOH. Also, linking socioeconomic policies to health outcomes is not a new phenomenon. Adler and Newman (2002) discussed several policies that are designed to directly impact an individual's socioeconomic status such as labor-market policies, redistributive policies and policies affecting environmental exposures to name a few.

Labor market policies are geared around improving overall labor market outcomes while supporting and protecting the workers. Some policies related to labor market would be the fight for livable wages (i.e., increasing minimum wage), unemployment insurance, and transitions from manual low-skilled labor to STEM. Redistributive polices are policies where government funds are used to invest in reducing economic inequalities. Sometimes these types of polices can be looked at as being extreme liberal/socialist leaning, but this is not a new or extreme idea. As a matter of fact, programs like Head Start[11], food stamps and even Medicare can be viewed as redistributive policies. These policies allow low-income individuals to have an opportunity to be at the same level playing field as higher income individuals, thereby eliminating detrimental disparities that can negatively affect health outcomes. Policies affecting environmental exposures primarily consist of policies that aim to limit or eliminate pollution, promote clean air, and clean energy, and climate change. Often time, people of

[11] According to Benefits.gov, "Head Start is a Federal program that promotes the school readiness of children from birth to age five from low-income families by enhancing their cognitive, social, and emotional development. More details on program can be found at https://www.benefits.gov/benefit/616

color and low-income individuals live in areas that are highly impacted by hazardous environmental pollutants that ultimately have a negative effect on health outcomes. These policies amongst others, are not specifically healthcare policies but can impact an individual's health care.

VIII. Conclusion

This paper provides empirical evidence that SDOH causes unfavorable health outcomes which causes hospital inpatient cost to increase attributing to the erosion of hospital profitability. If the circumstances around those SDOH were improved, hospital profitability would improve. I assume that since the SDOH causes unfavorable effects on health outcomes, the improvements of those SDOH would improve health outcomes. Overall, I conclude that improving Violent Crime, SNAP and Unemployment by one standard deviation will result in hospital cost savings as follows: total hospital cost would decrease between 0.16% and 0.21% for Violent Crime, up to 0.5% for SNAP and between 1.2% and 1.7% for unemployment resulting in a favorable impact on hospital profitability. The dataset used in this analysis prevented me from being able to go more granular, so more detailed analysis at the state, city and zip code level would give a more precise estimation of possible cost savings related to SDOH improvements. This paper introduces IV analysis and found endogeneity with the SDOH variables and uses political affiliation as the instrument to isolate the exogenous portion of the SDOH.

There are few studies, if any, that directly ties the improvement of SDOH to hospital profitability. However, based on the findings in this paper, causality between SDOH and hospital cost has been established. The future research in this area would be vital for all hospitals and health systems and has the potential to change the trajectory of a plummeting bottom line.

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