High-frequency Mobility Data and Altman Z-Score: Assessing the COVID-19 Impact on Hospitals Financial Distress*

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(First Draft: May 10, 2021.)

The typical corporate financial ratios and operational indicators predicting financial distress and bankruptcy become available at quarterly or annual frequency. To provide a more timely assessment of hospital's financial stress in response to the COVID-19 pandemic, we use high-frequency daily mobility data on visits to healthcare facilities tracked by smartphones to predict operational indicators that are historically associated with hospital financial ratios. We calibrate an Altman Z-score model that allows us to estimate a stable relationship between operational indicators and hospital financial distress in the pre-pandemic period and use the traffic predicted operational indicators to assess the financial impact of the pandemic. We find that the pandemic affected hospital financial distress in 2020 differently according to their ownership structure. In particular, investor-owned hospitals experienced significantly more financial distress than others. We estimate that 27.55% of all hospitals became financially distressed in 2020, up 0.69 percentage points from 2019. In contrast, 37.80% of investor-owned hospitals are predicted to become financially distressed, up 5.86 percentage points from 2019. Since investor-owned hospitals are the main providers of specialty health care services such as psychiatric and acute long-term care, their increased financial distress can potentially result in long-term effects on the quality and quantity of health care provided to all communities, especially the rural ones.

Keywords: Mobility data, hospital financial distress, investor-owned hospitals.

JEL Codes: H73, I18, R12.

*We thank Maddalena Conte for excellent research assistance, and the *Hopkins Business of Health Initiative* the Carey Business School for financial support. Corresponding author: Phillip Phan, pphan@jhu.edu. We thank New Generation Research Inc. for providing the bankruptcy data.

1 Introduction

The financial condition of the hospitals not only affects social welfare through the services they provide and therefore are of the interest of the policy makers and various government agencies, it has attracted increasing attention from the capital markets as the investor-owned hospitals has become an important source of health care services in recent years. According to American Hospital Association (AHA thereafter), investor-owned hospitals account for about 28% of the total hospitals, providing about 20% of the hospital beds, 16% of the emergency room visits, and about 16% of the inpatient and outpatient surgeries. Poor financial performance not only may result in bankruptcy, but also lead to the reduction in the quantity and the quality of the service provided. Understanding the financial challenges of the hospitals in a more timely manner can help the policy makers to react to change in the healthcare service provisions more effectively and efficiently. The traditional corporate financial ratios and operational indicators used to predict financial distress and bankruptcy, however, are typically available at quarterly or annual frequency. It does not serve the public's interests very well, for example, in a pandemic event like covid-19, which requires immediate and effective responses from the policy makers so to contain the damages.

To provide a more timely assessment of hospital's financial stress, we propose to use high-frequency daily mobility data on visits to healthcare facilities tracked by smartphones data. In essence, after estimating a stable relationship between operational indicators and distress from previous years in a logit model, we then use it along with our high-frequency mobility data predicted operational indicators, to estimate the impact of the pandemic on the probability of the hospitals' financial distress.

We focus on the measure and the estimation of the hospitals' financial distress instead of the actual bankruptcy event to provide more insights. Bankruptcy in general is not a frequent event. For example, there are 655,069 firms in the health care and social services industry in 2017 according to U.S. census data. The proprietary bankrupt data provided by New Generation Inc. suggests that the number of bankruptcy filings in the health care industry is 797 in 2017, accounting for 0.1% of the total firms. One possible reason that not all severe financial distress leads to bankruptcy filings is because of the government subsidiary and intervention. Analysis of bankruptcy data suggests that financial strain in the healthcare industry has been rising since 2017. It rose from 797 in 2017 to 937 in 2018 before it declined to 678 in 2019, which is still higher than the average level (564) of bankruptcy filings during the period of 2012 and 2016, according to the New Generation Inc. bankruptcy data. One may expect a surge of bankruptcy filings in the healthcare industry in 2020 due to covid-19, at least suggested by anecdotal evidence. For example, Bloomberg reported that more than three dozen hospitals have entered bankruptcy up until Sept 2020 (Bloomberg 2020), and more than a dozen of hospitals in the rural areas (Cecil G. Sheps Center for Health Services Research at the North Carolina).

The actual default data provided by the New Generation Inc. however, has run surprisingly below earlier expectations. We find that the number of bankruptcy filings in the healthcare industry sums to 753 in total in 2020, which has increased from 2019 but still below the level in peak year of bankruptcy filings in 2018. The incomplete data of the first quarter of 2021 shows 88 fillings in total, suggesting no indication of a surge of bankruptcy in the healthcare industry as the covid-19 effects continues to unfold. This is possibly due to U.S. Federal government assistance for hospitals that might have slowed the failure of the financially weak hospitals and helped otherwise financially healthy ones to withstand the COVID-19 shock.

The financial pressures of COVID-19 however can't be measured just by the actual filings of bankruptcy. The American Hospital Association (AHA) projected that the hospital and health system financial losses were expected to be at least $323.1 billion in 2020. Consulting firm Kaufman Hall projected that hospital margins could sink to -7% in the second half of 2020, and more than half of all hospitals were predicted to have negative margins during the fourth quarter of 2020.

Furthermore, the increased financial distress among hospitals may result in severe consequences other than the bankruptcy filing. For example, early evidence suggested that hospitals have been closing low acuity hospital beds, cancelling elective procedures, outpatient clinic encounters, and other non-COVID-19 services. U.S. has 2.8 hospitals beds per 1,000 compared to 3.2 in Italy, 6.1 in France, and 12.0 in South Korea (Peterson Center on Healthcare 2020). Compared to its OECD counterparts and developed Asian economies, this suggests that the U.S. healthcare system is already operating at the frontier of its capacity constraints. Hence, any reduction in capacity due to unexpected shocks or loss of financing serve to exacerbate an already tenuous situation for U.S. patients. Hospitals provide other benefits to their communities as well, including improving community and population health including medical research and subsidizing high-cost. Hospitals reported total community benefits of over $100 billion, or 13.8% of total expenses (AHA, 2020). Hospitals' and health systems' role in their communities is larger than just a health care provider – they are often economic anchors. Being able to assess hospitals' financial condition more frequently may help to reduce the negative impacts of the financial deterioration on the community.

To carry out our research plan, we first classify hospitals as financially distressed using Altman Z-score modified to model both public (listed) and private (unlisted) cooperates operating in any sector of the US economy as in Altman (1983). We then estimate a logit model for the dummy variable indicating financial distress, linking it to financial and operational indicators from the American Hospital Association Annual Survey from 2011-2019. Next, we exploit daily mobility indicators for more than 3000 hospitals to predict the 2020 values of hospital operational indicators in a simple forecasting regression. We find that mobility data forecast well in sample and the logit distress model with predicted operational data for 2018 and 2019 does slightly better than the logit distress model using the actual values of the operational data for 2018 and 2019. Lastly, we use the predicted values of operational indicators to forecast financial distress in 2020 and study its distribution by the types of hospitals such as the ownership types, the service types and the demographic characteristics.

Overall, consistent with the pattern of the bankruptcy filings, there is not much change in the financial distress of the hospitals in 2020. We however find that the pandemic affected hospital financial conditions in 2020 differently according to their ownership structure. In particular, investor-owned hospitals experienced significantly more financial distress than others. Specifically, we predict/estimate that 27.55% of all hospitals became financially distressed in 2020, up 0.69 percentage points from 2019. In contrast, 37.80% of investor-owned hospitals are predicted to become financially distressed, up 5.86 percentage points from 2019. Since investor-owned hospitals are the main providers of specialty health care services such as psychiatric and acute long-term care, their increased financial distress can potentially result in long-term effects on the quality and quantity of health care provided to all communities, especially the rural communities that have already had limited access to specialty health care in the pre-pandemic period. If the increased financial distress among the investor-owned hospitals led to the reduced services or even closure of the facilities, it means that patients in the rural area would need to travel even further and/or wait longer to receive the care needed.

There are different potential explanations. When it comes to the operational indicators, generally speaking, we observe that inpatient surgeries and inpatient visits reduce financial distress, the other types of visits such as outpatient surgeries, outpatient visits and emergency visits, increase financial distress. Different hospitals react to operational factors in different ways. For example, government hospitals rely on inpatient days much less (half) than other hospitals to stay solvent. So the reduction in traffic in 2020 will have less negative impact on them. Additionally, Government hospitals is more harmed by emergency room visits than other types according to the patterns suggested in the pre-pandemic period. The reduced traffic in 2020 may help them relieve from the financial burden because of treating the emergency visits. Investor-owned hospitals, on the contrary, rely significantly more on both inpatient surgeries and inpatient visits to enhance financial performance thus reduce the likelihood of experiencing financial distress. The less such visits/services due to covid-19 will hurt them more profoundly.

Note here that investor-owned hospitals are also the main providers of special treatments such as Psychiatric (48 percent are investor-owned), acute long-term care (76 percent are investor-owned), and rehabilitation (79 percent are investor-owned). The increased financial distress in investor-owned hospitals, therefore, would have long-term impact on patients seeking these special treatments.

We also find that although in general there is not much change in hospital distress, health providers in different categories may feel the Covid-19 shock differently. We find that providers such as children's orthopedic, intellectual disabilities, children's psychiatric, psychiatric ,acute long-term care hospitals, and the rehabilitation for example, are the the groups that experience the most distress. The failure of these health providers would have a long-term negative impact on the patients in need.

Last but not the least, the real effects of the financial distress of hospitals and medical providers could materialize in terms of loss of service provision at a time when it is most needed. And these effects could be disproportionately felt in suburban and rural communities that can least afford to lose access to health care. Although our results suggest that rural hospitals experience much less financial distress both historically and in 2020, the majority of rural hospitals are general medical and surgical hospitals, which are known to be less financially challenged than other types of hospitals. Patients living in rural areas seeking specialty treatment, therefore, have to travel to such health providers located in urban areas before the Covid-19 pandemic. The increased financial distress or even the closure of the special care service providers thus not only affect patients living close by, but also the patients living in rural areas because they will have to travel even further to receive treatment, letting alone the increased waiting list.

Our study contributes to the literature on the economic stability of the health care sector, which has been studied either in other countries, or at the state level only. Langabeer et al. (2018) quantify the financial distress in acute care hospitals in Texas in the period 2012-2015, using the American Hospital Association's (AHA) Annual Survey Database as we do. They calculate the Altman z-score for every hospital in the sample for each study year. They then fit a binary logistic regression model to identify hospital factors associated with distressed hospitals, and find distressed hospitals tend to have less outpatient revenue, lower patient acuity, and fewer beds. Puro et al. (2019) compare the accuracy of three financial distress prediction models (the modified Altman Z score, the Ohlson O score and the Zmijewski score), and their ability to predict bankruptcy for US acute care hospitals, using AHA and Medicare cost reports data. Holmes et al. (2017) studies determinants of financial distress among U.S. rural hospitals. Holmes et al. (2017) studies determinants of financial distress among U.S. rural hospitals. Our paper contributes to the branch of this literature by providing a more timely assessment of hospital's financial stress. Using high-frequency daily mobility data on visits to healthcare facilities tracked by smartphones to predict operational indicators, we can predict the financial distress more frequently.

Another literature our paper contributes is the one on COVID-19, which is large and growing rapidly [1]. Studies have highlighted the decrease in non-COVID-19 hospital visits during the current pandemic across the world (Alé-Chilet et al., 2020; Engy Ziedan and Wing, 2020). This is likely to have had a large negative impact on cash flows and the financial stability of hospitals and other health care providers (Kruse and Jeurissen, 2020; Khullar et al., 2020). Our paper contributes to the branch of this literature that focused on the COVID impact on hospital financial distress. Our analysis not only provide financial outlook of the hospitals but also the implications on the service provision and patient impacts.

The remaining of the paper is organized as the following. Section 2 describes the data. Section 3 explains the methodology. Section 4 reports the results of the historical relationship between financial distress and operational indicators and the predicted operational indicators using the high-frequency mobility data. Section 5 shows the predicted financial distress in 2020 using the mobility data estimated operational indicators. Section 6 discusses the implications of financial distress on service provisions. Section 7 concludes.

[1] See Brodeur et al. (2020) for a recent survey

2 Data

We use the American Hospital Association (AHA) Annual Survey as the main source of financial and operational data on healthcare facilities. The AHA annual survey reports information for all hospitals on their annual income statements and balance sheets as well as typical operational indicators used in the credit risk analysis of hospitals. We use annual data from this survey for the period 2011-2019. Specifically, we consider the following operational variables: inpatient surgeries, outpatient surgeries, inpatient days, emergency room visits, and outpatient visits. The other hospital characteristics we retrieve are the percent of outpatient revenue, the hospital type of ownership (government, nonprofit, or investor-owned), whether it is a teaching hospital, a rural hospital, the number of hospital beds, the number of full-time employees, the number of full-time physicians, airborne isolation capabilities, the number of air rooms, whether it belongs to a hospital system, and the hospital case mix index (CMI).

Data on hospital costs reported to Medicare through the Healthcare Provider Cost Reporting Information System (HCRIS) complement AHA data. We use these sources to parametrize the Altman Z-score card.

We use the AHA to predict financial and bankruptcy risk. The models are trained using proprietary data on bankruptcies and related court actions from New Generation Research and

To assess hospital's financial conditions at a higher frequency, we forecast the lower-frequency operational variables typically used in the analysis of hospital credit risk with indicators based on cell-phone mobility data. Unlike statistics based on patient records, these area available at a daily frequency and available every week. Mobile phone location data is provided by SafeGraph. The data covers about 45 million devices, 16% of all smartphones in the U.S (coverage calculated using Jan 2020). Tracking the devices' pings, the data identifies visits to any point of interest (POI). Visits to points of interest (POIs) are aggregated by category (e.g. restaurants, bars, schools, etc.) using Google Places classification (Goolsbee and Syverson, 2021). Safegraph provides comprehensive coverage of all areas in the US. Mobility data are an accurate proxy for the level of economic activity at the establishments or POIs tracked, as has been documented widely for other economic sectors

(Chetty et al., 2020). Couture et al. (2021) show that smartphone mobility data are representative of movement patterns in the United States and match well conventional survey data. We match mobility data to hospital addresses in the AHA database to get a dataset of visits to hospitals. The matching is verified using Google places classification of all location building polygons tracked by Safegraph.

We construct three samples of data on visits to healthcare facilities, with increasing matching stringency requirements with respect to the location types we track visits to. The first sample uses the full list of AHA hospitals, matches their addresses to building polygons and counts visits to those polygons, regardless of their classified type by Safegraph (using Google Places). This sample possibly includes buildings whose main purpose has been classified as non-hospital POIs, i.e. coffee shops. This could happen when there are other POIs in the same building as the hospital, i.e. a coffee shop inside a hospital. Traffic to this POI may be included as hospital traffic in this broad sample. This sample results in visits tracked to 4,833 locations, or 86% of all AHA hospitals.

The second sample, restricts the identified visits to only building polygons that are also classified by Safegraph as a medical facility (including hospitals, outpatient centers, psychiatric centers and physicians offices). This results in visits tracked to 4,633 locations.

The third sample restricts the identified visits to those in building polygons classified by Safegraph specifically as General Medical and Surgical Hospitals. This results in visits tracked to 3,441 locations.

Table 1 shows the total number of hospitals in our AHA dataset by year. The rows for 2011-2019 show the distribution of hospitals using AHA data. The rows for 2020 shows the distribution of the hospitals for which we track visits using mobility data. This number represents 90% of all hospitals in the United States, which suggests that our study data is a good representation of the sector.

About half of all the hospitals are non-profit, while investor-owned hospitals constitute between 25% and 28% of hospitals. The remaining 20%-25% of hospitals are government-owned. Most non-profit hospitals are hospitals originally established by religious groups or philanthropists. Non-profit hospitals have no shareholders and are subject to the non-distribution constraint—profit

Table 1: Hospitals by year and by ownership

Year	Total Hospitals	Investor_owned		Non-profit		Government_owned	
2011	5,608	1,514	27.00%	2,954	52.67%	1,140	20.33%
2012	5,653	1,563	27.65%	2,957	52.31%	1,133	20.04%
2013	5,632	1,548	27.49%	2,979	52.89%	1,105	19.62%
2014	5,605	1,565	27.92%	2,945	52.54%	1,095	19.54%
2015	5,585	1,564	28.00%	2,941	52.66%	1,080	19.34%
2016	5,560	1,574	28.31%	2,944	52.95%	1,042	18.74%
2017	5,582	1,580	28.31%	2,964	53.10%	1,038	18.60%
2018	5,543	1,560	28.14%	2,950	53.22%	1,033	18.64%
2019	5,793	1,526	26.34%	3,067	52.94%	1,200	20.71%

cannot be distributed to shareholders and must be committed to advance charitable, education, or other missions (Fama and Jensen, 1983). Nonprofit hospitals are generally exempted from federal and state income taxes, property taxes, and sales tax (Bai et al., 2021). Investor-owned hospitals are for-profit entities with the objective to maximize investors' value. THey operate as corporations or partnerships. Tax-exempt status is not applicable to investor-owned hospitals (Bai et al., 2021). Government-owned hospitals are federal, state, or local government agencies. Government-owned hospitals face a soft budget constraint (Eldenburg and Krishnan, 2008). They are subsidized by tax revenue and do not distribute profit. The shares of non-profit and investor-owned hospitals have slightly increased between 2011 and 2019, while the share of government-owned hospitals has slightly decreased.

Table 2 shows descriptive statistics for key variables. Appendix A provides details for more variables for each of the hospital types. We include these variables in regressions as controls.

Table 2: Descriptive Statistics

Panel A: Resources				
Item	Mean	SD	Min	Max
Full-time physicians	23	97	0	2,890
Full-time employees	908	1,546	7	32,397
Hospital beds	151	188	1	3,890
Airborne Isolation	0.578	0.494	0	1
Air rooms	7	15	0	388
Teaching	4.88%	21.55%	0	1
Rural	16.56%	37.17%	0	1
System	63.76%	48.07%	0	1
Panel B: Operating Activities				
Item	Mean	SD	Min	Max
Emergency Room Visit	23,533	32,634	0	617,780
Outpatient Visits	135,361	244,180	0	8,091,607
Inpatient Surgeries	1,533	2,832	0	49,190
Outpatient Surgeries	3,104	5,027	0	138,765
Total Inpatient Days	35,979	52,128	1	775,202
Panel C: Financial Performance				
Item	Mean	SD	Min	Max
Z score	6.032	7.806	-7.525	26.497
Financial distress	24.58%	43.06%	0	1
Leverage	0.468	0.469	-0.579	1.526
NI/TA	0.058	0.154	-0.24	0.439
Outpatient revenues (%)	51.32%	26.75%	0	1

3 Methodology

In our empirical analysis, we take the following four steps. First, we use Altman Z-score (Altman, 1968) approach to identify hospitals financial distress based on 2011-2019 data. Second, we estimate a logit model for a financial distress dummy variable based on the first step. Third, we predict operational variables in 2020 with high-frequency mobility data. Fourth, we use the estimated logit model parameters and the predicted values of the hospital operational to predict the probability of hospital financial distress in 2020. Finally, we discuss the impact of hospital financial distress on health service provisions in 2020. We now discuss each of these four steps in more detail.

3.1 Measuring Hospitals Financial Distress

The Altman Z-score (Altman, 1968) is a widely used distress indicator by both researchers and practitioners for predicting business failure. The original Altman Z-score is a weighted index of five financial ratios: liquidity, profitability, leverage, solvency, and activity. The original score-card relied only public firm data, but Altman (1983) re-estimated it including both public (listed) and private (unlisted) firms. Since most hospitals in our sample are unlisted corporations, in our application we use the 1983 specifications adapted to cover also private corporations in which leverage is measured by book value of equity to total liabilities. Another major adjustment made by Altman (1983) is to drop the turnover ratio (sales/total assets) so as to apply the the model also to non-manufacturing businesses. Altman et al. (2017) validates this four-factor Z-score model using public and private firms in non-financial industries across all sectors from 34 countries and finds it performs well in predicting financial distress, with a classification accuracy above 90 percent.

The four-factor Altman (1983) Z-score model is:

$$Z_{it} = 6.56A_{it} + 3.26B_{it} + 6.72C_{it} + 1.05D_{it}, \tag{1}$$

where A is working capital over total assets, B is retained earnings over total assets, C is earnings before interest and tax over total assets, D is book value of equity over total liabilities. We compute the Z-score for each hospital in each year provided the required information is available.

Next, following the literature (Altman (1968, 1983); Altman et al. (2017), Langabeer et al. (2018)), we assign a value of one to the hospitals with Z-score values less or equal to 1.80, thus classifying them in distress, and zero otherwise. Then, similar to Langabeer et al. (2018), we run a logit regression to identify the hospital and operational variables and characteristics that predict financial distress for each of the three types of the hospitals according to the ownership structure from 2011 to 2019.

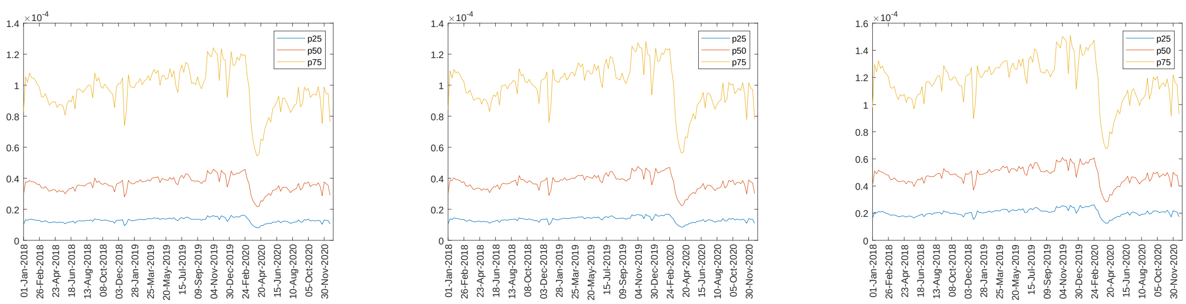
The specification is as follows.

$$Distress_{it} = \alpha + \lambda_l + \gamma_s + \theta_t + \sum \beta_i * X_i + \sum H_i * D_j + \epsilon_{it}, \tag{2}$$

where α is the constant term, λ_l is a county fixed effect, γ_s is a service-type fixed effect, θ_t is a year-fixed effect, and X_i are the five hospital operational indicators discussed above: (i) inpatient surgeries, (ii) outpatient surgeries, (iii) inpatient days, (iv) emergency room visits and (v) outpatient visits H_i is a vector of annual hospital characteristics: (a) percent of outpatient revenues, (b) teaching hospital, (c) rural hospital, (d) hospital beds, (e) full-time employees, (f) full-time physicians, (g) airborne isolation equipped, (h) air rooms, (i) whether it belongs to a system or not, and (j) the CMI index when available.

3.2 Predicting Operational Indicators with Mobility Data

Since usually there is a lag in the publication of the financial performance and operational indicators of corporations, and hospitals in particular, we use high-frequency mobility data to predict their level of activity and gain a timely insight into their financial conditions.



(a) Sample 1 (b) Sample 2 (c) Sample 3

Figure 1: Unique Weekly Visits to Hospital POIs

NOTE. The figure shows weekly time series from January 1st 2018 to December 31st 2020, for total unique visits to hospitals POIs. The three panels plots total visits by quartile for of the three samples discussed in section **REFERENCE**. Hospital-specific time series are normalized using the number of devices seen by Safegraph each week.

Figure 1 shows weekly time series, from 01-Jan-2018 until 31-Dec-2020, of total unique visits to hospitals POIs normalized by number of devices tracked, by distribution quartile, in each of the three samples discussed above. The figure, therefore, plot mobility to hospitals during 2020 and two year priors, clearly illustrating the sheer magnitude of the COVID-19 shock. The figure also highlight a very mild pre-COVID-19 trend growth, and marked heterogeneity across hospitals both before and after the COVID-19 shock.

We use this hospital-specific variable to forecast hospital hospital operational indicators. We consider three predicting specifications

$$Y_{iht} = \alpha + \gamma_c + \beta * X_{ht} + \epsilon_{iht}, \tag{3}$$

$$Y_{iht} = \alpha + \gamma_c + \theta_h + \beta * X_{ht} + \epsilon_{iht}, \tag{4}$$

$$Y_{iht} = \alpha + \gamma_c + \beta_1 * X_{ht} + \beta_2 * \Delta X_h + \epsilon_{iht}, \quad with \quad \Delta X_h = X_{h2020} - X_{h2019} \tag{5}$$

where α is the constant term, γ_c is the state fixed effect, θ_h as a hospital fixed effect, X_{ht} is total annual visits to hospital h, and ϵ_{iht} is the forecast error term. Remember here that $i =$ OpIndicator, $h =$ hospital, $t =$ year.

The first two specifications predict the level of the each hospital operational indicator with the cumulative annual visit and pool the data for the two years for which we observe both mobility data and hospital operation indicators from the AHA survey, 2018 and 2019. The difference between the first and the second specification is the inclusion of the hospital fixed effect, θ_h, The third specification is dynamic, and considers both the 2019 level and the change between 2020 and 2019. In all three specification, the critical assumption is that visit to hospitals is a *common factor* that drives hospital performance, with different operational indicators loading differently on it.

We then use the predicted value of our operational variables to estimate the likelihood of financial distress in 2020 relying the coefficients estimated from a logit model for the probability of financial distress estimated on historical data, from 2011 to 2019, repeating the exercise for each of the three matched samples that we discussed above. So we produce results for nine specifications in total and, as we will see, we remarkably robust results.

4 Historical Hospital Financial Distress Predictors

Using historical data from the AHA Annual Survey comprising nearly all hospitals in United States from 2012 to 2019, we run a logit regression analysis of the predictors of hospital financial distress. The results are reported in Table 3. The dependent variable is the dummy indicator of financial distress. A hospital is classified as financially distressed, and the dummy takes on the value of one, if the computed Z-score is below 1.80. All models control for year fixed effects, the service type effects (whether it is a general hospital or a specialty hospital), and the state fixed effects, except that model 2 excludes year effects.

Table 3: Logit Modeling of Hospital Financial Distress

Variables	**(1)**	**(2)**	**(3)**	**(4)**
Investor	0.612***	0.363***	0.363***	0.470***
	(20.26)	(11.10)	(11.09)	(11.06)
Government	0.256***	0.176***	0.176***	0.247***
	(8.28)	(5.06)	(5.05)	(4.89)
Inpatient surgeries		-0.0556**	-0.0571**	-0.0852
		(-2.18)	(-2.24)	(-1.51)
Outpatient surgeries		0.0511**	0.0516**	-0.0176
		(2.31)	(2.33)	(-0.35)
Inpatient days		-0.444***	-0.441***	-0.142
		(-7.61)	(-7.58)	(-1.28)
Emergency room visits		0.108***	0.105***	0.147***
		(5.17)	(5.01)	(4.41)
Outpatient visits		0.0366**	0.0398**	0.0145
		(2.30)	(2.49)	(0.28)
Outpatient revenues (%)		-1.566***	-1.623***	-1.491***
		(-15.83)	(-16.24)	(-9.44)
Teaching		0.336***	0.345***	0.466***
		(4.73)	(4.84)	(6.07)
Rural		-0.271***	-0.277***	-0.433***
		(-7.67)	(-7.82)	(-7.96)
Hospital beds		0.621***	0.640***	0.415***
		(6.79)	(7.00)	(2.87)
Full-time employees		-1.129***	-1.169***	-1.470***
		(-14.34)	(-14.73)	(-10.40)
Full-time physicians		0.151***	0.166***	0.187***
		(6.15)	(6.69)	(6.31)
Airborne isolation		-0.0690**	-0.0604**	-0.145***
		(-2.46)	(-2.15)	(-3.71)
Air rooms		-0.00854***	-0.00877***	-0.00536***
		(-6.17)	(-6.30)	(-3.60)
System		0.170***	0.162***	0.311***
		(6.21)	(5.91)	(8.13)
CMI				-0.117
				(-1.62)
Constant	-0.880***	3.011***	3.056***	3.491***
	(-11.53)	(16.20)	(16.30)	(11.20)
Year effects	Yes	No	Yes	Yes
Service type effects	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes
Pseudo-R2	0.0523	0.0743	0.0751	0.0914
P>chi2	0.000	0.000	0.000	0.000
N	49718	49420	49420	28321

NOTE. The table reports a logit regression results for different specifications using historical annual AHA survey data from 2011 to 2019. The dependent variable is a dummy taking value of one when the Z-score is less than 1.80. Each column report a different specification. Column 1 predicts hospital distress only based on the hospital ownership type. Columns 2 and 3 include ownership type, operating activities, hospital resources and financial performance (outpatient revenues) variables? Column 2 does not include the year fixed effects. Column 4 includes also the hospital CMI index. All specifications also include a location dummy which indicates if the hospital is located in rural areas.

We are particularly interested in the predicting power of the hospital ownership status: nonprofit, investor-owned, and government (both state and federal) hospitals. The specification in column 1 shows that both investor-owned and government hospitals experience significantly higher financial distress than nonprofit hospitals, especially investor-owned hospitals. The coefficient of investor-owned (government) hospital is 0.612 (0.256), both significant at 1% level. The predictive power of ownership status survives after we include operational indicators and all other control variables.

The share of outpatient revenue helps to reduce financial distress significantly. Panel C of Table 2 shows that outpatient revenues accounts for 51.3% of the total revenue during our sample period of 2011 and 2019. It has been increasing steadily over time since the mid 1990s, driven by advances in clinical technology, the consumers' preferences for outpatient services due to the convenience and lower out-of-pocket cost, the pressure from Medicare, Medicaid and commercial plans to shift care away from inpatient-settings, and the acquisition of physician practices to deliver outpatient care at their facilities.[2]

The five included operational variables also are significant predictor of financial distress. The specifications in columns 2 and 3 show that, controlling for the percent of the outpatient revenues and other hospital characteristics, inpatient surgeries and inpatient days are associated with lower financial distress, while outpatient surgeries, emergency room visits, and outpatient visits increase expected financial distress. The sharp difference between the impact of inpatient and outpatient services on hospital distress suggest some major differences in the cost structure between these two types of services. The cost of outpatient care such as X-Rays, MRIs, typically consists of fees related to the doctor or the particular test performed; the cost of inpatient care for surgeries and serious illness that require substantial monitoring includes facility-based overhead in addition to the job specific expenses. As hospitals bridge the gap in services by providing general medical care to outpatients, allocating costs to outpatient related services just by job-related costs (direct costs such as physicians and materials or depreciation of the equipment involved in the particular test) may not correctly reflect the true cost of providing such services if they are still conducted within the hospital facilities.

[2] Outpatient revenue has grown from 28% in 1994 to 49.1% of the total in 2012 according to a study by the Deloitte Center for Health Solutions[3].

Table 3 also shows that Rural hospitals experience significantly lower financial distress holding everything else constant. This may first seem to contradict the popular narrative in the business press that rural hospitals face greater financial challenges.[4] Our results are not in line with anecdotal evidence, based on the survived rural hospitals in our sample. The reason is that about 99.8% of the rural hospitals are general medical centers. General medical centers, however, compared to other specialty hospitals, suffer the lowest financial distress. The relatively stronger financial position of rural hospitals, however, does not tell the whole story about service provision to rural community, as we will discuss in the last section of the paper.

4.1 Results by Hospital Types

Next we repeat the same logit analysis splitting the sample by type of ownership to evaluate the interaction between ownership status and the individual predictors. The results are reported in Table 4. We find that hospitals with different ownership type are affected by operational indicators differently.

Investor-owned hospital's financial distress benefit particularly in terms of lower likelihood of financial distress from inpatient surgeries and inpatient days compared to the other two types of hospitals. After controlling for year fixed effects, investor-owned hospitals are the only type of hospitals that experience less financial distress with more inpatient surgeries. The coefficient as shown in column 2 is -0.192, significant at 1% level. The coefficient for inpatient days is -0.622, much higher than the -0.362 for government hospitals, highlighting the importance of inpatient care to the bottom line of the investor-owned hospitals.

Another distinct pattern shown in Table 4 for investor-owned hospitals is that while belonging to a hospital system increases the financial distress of the nonprofit and government hospitals, it decreases predicted distress for investor-owned hospitals. It suggests that investor-owned hospitals are more likely to benefit from economies of scope of being with system than the other types of the hospitals.

Results presented earlier in Table 3 show that teaching hospitals are associated with higher

[4]See, for instance, https://www.wsj.com/articles/a-citys-only-hospital-cut-services-how-locals-fought-back-11618133400?mod=searchresults$_pos1page = 1 according to which over 130 rural hospitals closed nationwide between 2010 and$ **DATE**.

Table 4: Logit Modeling of Hospital Financial Distress by Ownership Type

Variables	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		Investor			**Government**			**Nonprofit**	
Inpatient surgeries	-0.165***	-0.192***	-0.211*	-0.119**	-0.0867	-0.0370	-0.0417	-0.0356	-0.140
	(-3.63)	(-4.14)	(-1.86)	(-2.09)	(-1.52)	(-0.29)	(-0.98)	(-0.84)	(-1.60)
Outpatient surgeries	0.0964***	0.119***	0.229**	-0.000509	-0.0292	-0.0537	0.0420	0.0399	-0.218***
	(2.76)	(3.35)	(2.33)	(-0.01)	(-0.55)	(-0.43)	(1.10)	(1.04)	(-2.93)
Inpatient days	-0.636***	-0.622***	0.0559	-0.388***	-0.362***	0.320	-0.617***	-0.623***	-0.423**
	(-4.87)	(-4.74)	(0.28)	(-3.40)	(-3.19)	(1.11)	(-6.59)	(-6.66)	(-2.49)
Emergency room visits	0.156***	0.159***	0.193***	0.172***	0.211***	0.387**	0.0196	0.0180	0.0701
	(5.60)	(5.68)	(4.22)	(2.60)	(3.09)	(2.08)	(0.52)	(0.47)	(1.16)
Outpatient visits	0.0623***	0.0584***	-0.184*	-0.0578	-0.0543	0.107	0.105**	0.109***	0.0678
	(3.17)	(2.97)	(-1.76)	(-1.25)	(-1.14)	(0.51)	(2.52)	(2.62)	(0.75)
Outpatient revenues (%)	-1.074***	-1.040***	-0.730**	-1.738***	-2.024***	-1.588***	-2.016***	-2.087***	-2.174***
	(-6.53)	(-6.31)	(-2.46)	(-7.05)	(-8.11)	(-3.59)	(-12.68)	(-12.97)	(-9.58)
Teaching	0.428	0.422	0.703**	1.118***	1.185***	1.339***	0.125	0.133	0.145
	(1.48)	(1.47)	(2.24)	(6.55)	(6.96)	(6.81)	(1.37)	(1.46)	(1.47)
Rural	-0.545***	-0.562***	-0.781***	-0.0557	-0.0703	-0.389***	-0.153***	-0.154***	-0.270***
	(-5.29)	(-5.44)	(-5.53)	(-0.84)	(-1.05)	(-3.45)	(-3.09)	(-3.10)	(-3.65)
Hospital beds	0.781***	0.811***	0.555**	-0.160	-0.109	-0.544	0.980***	0.999***	0.794***
	(4.57)	(4.72)	(2.24)	(-0.82)	(-0.56)	(-1.34)	(6.70)	(6.82)	(3.66)
Full-time employees	-0.878***	-0.927***	-1.408***	-0.362**	-0.560***	-1.548***	-1.450***	-1.490***	-1.529***
	(-6.01)	(-6.31)	(-5.25)	(-2.05)	(-3.14)	(-4.84)	(-10.88)	(-11.10)	(-7.06)
Full-time physicians	0.327***	0.375***	0.378***	0.184***	0.208***	0.205**	0.150***	0.162***	0.192***
	(5.27)	(5.79)	(4.54)	(2.96)	(3.31)	(2.53)	(4.66)	(4.98)	(5.10)
Airborne isolation	0.156***	0.161***	0.0556	-0.346***	-0.338***	-0.484***	-0.143***	-0.134***	-0.151***
	(2.87)	(2.97)	(0.74)	(-5.41)	(-5.23)	(-4.52)	(-3.32)	(-3.10)	(-2.67)
Air rooms	-0.0253***	-0.0249***	-0.0194***	-0.00364	-0.00470	-0.000323	-0.00813***	-0.00839***	-0.00611***
	(-5.46)	(-5.39)	(-3.60)	(-1.30)	(-1.64)	(-0.10)	(-4.59)	(-4.70)	(-3.19)
System	-0.269***	-0.266***	-0.236***	0.285***	0.258***	0.487***	0.296***	0.285***	0.361***
	(-4.70)	(-4.64)	(-2.68)	(4.37)	(3.94)	(4.82)	(7.67)	(7.36)	(7.02)
CMI			-0.535***			-0.119			0.143
			(-4.63)			(-0.49)			(1.15)
Constant	3.021***	3.120***	3.400***	3.078***	2.947***	1.895**	4.054***	4.140***	5.204***
	(8.67)	(8.89)	(6.00)	(7.77)	(7.31)	(2.33)	(13.06)	(13.22)	(11.14)
Year effects	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
Service type effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo-R2	0.0597	0.0610	0.0958	0.138	0.148	0.182	0.0887	0.0893	0.0941
P>chi2	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	13743	13743	6771	9503	9503	3913	26058	26058	17320

Note. The table reports results splitting the full sample by type of ownership: Investor, Government and Nonprofit. All specifications are the same as in Table 3 except that they omit the ownership-type dummy. See Table 3 for more details.

financial distress. Results in Table 4 show that this is particularly driven by government-owned teaching hospitals. There are about 50 government owned teaching hospitals in our sample, and the average distress is 29.97%, higher than the average distress of government owned hospitals at 24.56%, and higher than the average distress of the teaching hospitals at 17.84%.

Table 5: Logit Modeling of Hospital Financial Distress: Rural vs. Urban

	(1)	(2)	(3)	(4)
	Rural		**Urban**	
Investor	0.340***	0.0305	0.363***	0.504***
	(3.11)	(0.19)	(10.46)	(11.31)
Government	-0.0322	-0.350**	0.251***	0.348***
	(-0.42)	(-2.49)	(6.33)	(6.32)
Inpatient surgeries	-0.000711	0.0696	-0.0368	-0.0984
	(-0.01)	(0.53)	(-1.23)	(-1.50)
Outpatient surgeries	0.0415	-0.0288	0.0511**	-0.0221
	(0.83)	(-0.24)	(2.00)	(-0.38)
Inpatient days	-0.213*	0.380	-0.556***	-0.209*
	(-1.75)	(1.24)	(-7.89)	(-1.69)
Emergency room visits	0.375***	0.256*	0.0922***	0.155***
	(3.36)	(1.89)	(4.31)	(4.45)
Outpatient visits	-0.135	0.434***	0.0358**	-0.0242
	(-1.12)	(2.63)	(2.23)	(-0.43)
Outpatient revenues (%)	-2.485***	-3.134***	-1.542***	-1.340***
	(-6.38)	(-4.36)	(-14.73)	(-8.16)
Teaching	0.603*	0.199	0.326***	0.459***
	(1.84)	(0.52)	(4.43)	(5.84)
Hospital beds	-0.147	-0.869**	0.843***	0.589***
	(-0.70)	(-2.02)	(8.03)	(3.76)
Full-time employees	-1.885***	-2.804***	-1.125***	-1.425***
	(-7.93)	(-6.57)	(-12.88)	(-9.31)
Full-time physicians	0.119	0.288**	0.166***	0.173***
	(1.49)	(2.49)	(6.30)	(5.58)
Airborne isolation	-0.0122	0.0872	-0.0734**	-0.147***
	(-0.16)	(0.52)	(-2.35)	(-3.57)
Air rooms	0.0106**	0.0196***	-0.0106***	-0.00673***
	(2.32)	(3.34)	(-7.07)	(-4.28)
System	0.387***	0.584***	0.0972***	0.258***
	(5.52)	(4.81)	(3.26)	(6.37)
CMI		-0.470		-0.0849
		(-1.29)		(-1.13)
Constant	4.891***	4.665***	3.054***	3.486***
	(8.56)	(4.51)	(14.62)	(10.32)
Year effects	Yes	Yes	Yes	Yes
Service type effects	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes
Pseudo-R2	0.123	0.131	0.0726	0.0912
P>chi2	0.000	0.000	0.000	0.000
N	8613	3464	40731	24770

NOTE. The table shows the results of the specifications of columns 2, 3 from 3, dividing the main sample on the hospital location, say rural or urban hospital. Hence, dropping the location dummy present on 3.

Table 6: Hospital Distress: Large vs. Small (divide by the average value of beds: Large >= 152)

	(1)	(2)	(3)	(4)
	Large		Small	
Investor	0.372***	0.459***	0.421***	0.469***
	(5.68)	(6.54)	(10.87)	(8.57)
Government	0.722***	0.585***	-0.00443	-0.0410
	(10.43)	(7.73)	(-0.11)	(-0.59)
Inpatient surgeries	-0.0196	-0.244*	-0.0320	-0.0524
	(-0.22)	(-1.78)	(-1.18)	(-0.81)
Outpatient surgeries	-0.132**	-0.174	0.0582**	0.0318
	(-1.97)	(-1.55)	(2.48)	(0.55)
Inpatient days	-0.187	-0.151	-0.188***	0.178*
	(-1.14)	(-0.80)	(-3.94)	(1.76)
Emergency room visits	-0.0307	0.0863	0.151***	0.185***
	(-0.53)	(0.90)	(6.56)	(4.75)
Outpatient visits	0.112***	0.140	0.0340*	-0.0282
	(2.72)	(1.36)	(1.95)	(-0.45)
Outpatient revenues (%)	-1.912***	-2.032***	-1.663***	-1.278***
	(-7.66)	(-7.05)	(-14.72)	(-6.55)
Teaching	0.271***	0.375***	0.742**	1.011***
	(3.29)	(4.32)	(2.38)	(2.75)
Rural	-0.439***	-0.471***	-0.212***	-0.336***
	(-4.58)	(-4.70)	(-5.46)	(-5.06)
Full-time employees	-1.119***	-1.141***	-1.034***	-1.562***
	(-6.29)	(-5.02)	(-12.25)	(-9.19)
Full-time physicians	0.196***	0.201***	0.0983***	0.116**
	(5.57)	(5.48)	(2.60)	(2.27)
Airborne isolation	-0.194***	-0.210***	-0.0740**	-0.113*
	(-3.19)	(-3.29)	(-2.13)	(-1.93)
Air rooms	-0.00530***	-0.00384**	0.00165	-0.00572
	(-3.09)	(-2.21)	(0.36)	(-0.86)
System	0.273***	0.298***	0.115***	0.298***
	(5.06)	(5.10)	(3.56)	(5.73)
CMI		-0.104		-0.111
		(-0.70)		(-1.28)
Constant	3.795***	4.240***	2.776***	2.992***
	(5.56)	(5.50)	(13.58)	(8.01)
Year effects	Yes	Yes	Yes	Yes
Service type effects	Yes	Yes	Yes	Yes
State effects	Yes	Yes	Yes	Yes
Pseudo-R2	0.101	0.0960	0.0744	0.100
P>chi2	0.000	0.000	0.000	0.000
N	15649	14253	33661	13936

NOTE. On table 6 we follow the same specifications of columns 2 and 3 from 3 but select samples of hospital size, that is, we divide each hospital beds by the total average of hospital beds, and, declare a hospital is large if the relationship > 152 3.

We also split the sample in rural and urban hospitals and report the same logit analysis in Table 5. Note that almost all rural hospitals (99%) are general medical centers and 93% of rural hospitals are either government (41%) or nonprofit (52%). For rural hospitals, being an investor-owned one, which is the exception rather than the rule, still increases the financial distress significantly. However, there is no significant difference in the financial distress between rural government and rural nonprofit hospitals, as shown in column 1 of Table 5. Another notable difference is the number emergency room visits that increases rural hospitals' financial distress significantly more than that of the urban hospitals. Rural hospitals are relatively smaller in terms of total hospital beds, full time employees, and full-time physicians. They receive much less emergency room visits on average than urban hospitals too. For example, in 2018, the average emergency visits for rural hospitals was 1,993, significantly lower than 3,608 per urban hospital **(see Table)**. But the analysis of the financial distress shows that emergency visits are financially more bothersome for rural hospital than urban ones.

To evaluate the role of hospital size in predicting financial distress, again, we split the sample into large vs small ones by the average value of total hospital beds. The results are reported in Table 6. These results suggest that large government hospitals are more financially stressed than other large hospitals, suggesting that government-owned hospitals may not benefit from economy of scale and scope. The coefficient of the inpatient days on financial distress is insignificant for large hospitals but significantly negative for small hospitals, suggesting that large hospitals, different from the small one, are less relying on inpatient days to ease its financial distress. This may indicate that large hospitals are more able to diversify revenue sources, benefit from advanced clinical technologies, and acquisition of physician practices.

4.2 Model Validation

Before proceeding to assess the impact of COVID-19 of the financial health of US hospitals out of sample, we want to evaluate the ability of our mobility-based indicator of hospital activity in **Figure REF** to predict hospital operational indicators in sample. To validate the approach proposed, we horse race the same baseline logit model estimated with the observed actual operational indicators from 2018 and 2019 with the same model estimated replacing 2018 and 2019 actual values with in their predicted counterparts, using one the three matched samples and the three predicting regressions discussed above.

Table 7 reports these in-sample model validation results. Column 1 of Table 7 uses the same specifications as the column 3 of Table 3, but estimated using only actual data for 2018 and 2019. The pseudo R2 using the observed indicators is 0.075. In models 2 to 10, we replace the five observed operational indicators in the benchmark model with the mobility-predicted counter part and keep all other variables the same. The reported Pseudo R2s for these alternative models is higher than in the benchmark for all 9 models, suggesting that the mobility-based predicted operational indicators work as well as the actual indicators.

Table 7: Model Validation: Logit Analysis for Hospital Distress Using Alternative Predicted Values of Operational Indicators for 2018 and 2019

	Benchmark: Column 3 in Table 3	**Traffic Model P1S1**	**Traffic Model P2S1**	**Traffic Model P3S1**	**Traffic Model P1S2**	**Traffic Model P2S2**	**Traffic Model P3S2**	**Traffic Model P1S3**	**Traffic Model P2S3**	**Traffic Model P3S3**
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Actual Operational Indicators	Yes	No	No	No	No	No	No	No	No	No
Mobility Pred. Operational Indicators	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control Variables	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R2	0.075	0.078	0.078	0.079	0.078	0.078	0.079	0.078	0.078	0.077
P>chi2	0	0	0	0	0	0	0	0	0	0
N	10,256	8,196	8,196	3,831	8,196	8,196	3,831	8,196	8,196	3,967

NOTE. The table reports the estimated pseudo R^2 for different models. Column 1 shows the pseudo R^2 for the benchmark model in column 3 of Table 3 that uses actual data. Columns 2 through 10 report the pseudo R^2 for nine models estimated using the 2018 and 2019 values of the predicted operational indicators obtained by using the three estimating equations in equations 3, 4 and 5, respectively and the three different sub-samples discussed in **Section REF**. All models include the SAME SET OF control variables from table 3 column 3.

To provide more direct evidence on the predicted distress, next, use the coefficients estimated from the dynmaic models 1, 4 and 7 that have the highest pseudo R2, combined it with the main operational indicators and other hospital characteristics to estimate the probability of each hospital's financial distress The average value of the estimated probability of financial distress of each method is presented in Table 8. The results confirms that using the mobility-based predicted

Table 8: Estimated distress in 2018 and 2019: Actual Operational Indicators vs. Traffic Predicted Indicators

	All Hospitals		**Nonprofit**		**Government**		**Investor**	
Model	2018	2019	2018	2019	2018	2019	2018	2019
Benchmark (Col. 3, Table 3)	23.55%	23.18%	19.43%	19.13%	22.37%	24.39%	32.45%	31.86%
EST Trafficp1s1	26.15%	27.74%	20.74%	22.98%	24.84%	26.96%	37.67%	37.78%
EST Trafficp2s1	26.10%	27.78%	20.94%	23.27%	24.46%	26.67%	37.41%	37.57%
EST Trafficp3s1	N.A.	26.02%	N.A.	21.41%	N.A.	25.92%	N.A.	35.20%
EST Trafficp1s2	26.27%	27.86%	20.84%	23.07%	24.89%	27.00%	37.88%	37.98%
EST Trafficp2s2	26.17%	27.85%	21.01%	23.34%	24.47%	26.69%	37.52%	37.67%
EST Trafficp3s2	N.A.	26.14%	N.A.	21.52%	N.A.	25.95%	N.A.	35.42%
EST Trafficp1s3	27.67%	29.16%	21.75%	23.90%	25.58%	27.64%	40.80%	40.77%
EST Trafficp2s3	26.49%	28.19%	21.38%	23.75%	24.43%	26.65%	38.00%	38.17%
EST Trafficp3s3	N.A.	27.38%	N.A.	22.28%	N.A.	26.49%	N.A.	38.18%

NOTE. The table compares the overall predicted hospital financial distress for 2018 and 2019 and by ownership type in for the benchmark model estimated based on actual data and 9 alternative models based on mobility-based predicted indicators.

indicators would generate comparable financial distress estimates as using the actual indicators in 2018 and 2019.

5 COVID-19 Impact on the Financial Health of Hospitals in 2020

We are now ready to evaluate the COVID-19 impact on the financial health of hospitals in 2020. We construct predicted operational indicators by using the 2020 value of our hospital specific mobility indicators to predict the five critical operational indicators. Then, using the previously estimated constant the state fixed effects, and the service code fixed effects for each ownership type of hospitals as shown in columns 1, 4 and 7 of Table 4, combined with the estimated coefficients with the mobility predicted operational indicators and the values of the other hospital characteristics from 2019, we compute the estimate probability of financial distress for each hospital with data in 2020.

The results are presented in Table 9. The table shows that the overall probability of distress in 2020 for the full sample of the hospitals is not deteriorating in 2020, consistent with evidence for bankrupcies in other sectors The estimated financial distress is 27.55% for the full sample, slightly

Table 9: Predicted Financial Distress in 2020

	2018 Observed	**2019 Observed**	**2020 Predicted**
All Hospitals	25.15%	28.09%	27.55%
Nonprofit	20.27%	22.64%	22.78%
Government	26.82%	32.11%	26.75%
Investor	32.44%	32.20%	37.61%

NOTE. NOTE HERE

down from 28.09% in 2019.

However, when we break down the sample by hospital type we find that hospitals with different ownership reacted to COVID-19 differently in 2020. Specifically, our estimates show that there is not much in the predicted financial distress of the nonprofit hospitals in 2020. The estimated distress is 22.78% for nonprofit hospitals in 2020, compared to 22.64% in 2019. Government hospitals are predicted to have a drop in the financial distress from 2019. The estimated distress is 26.75% for government hospitals in 2020, down from 32.11% in 2019. The investor-owned hospitals, however, are estimated to have a financial distress rate of 37.61% in 2020, 5.41 percent increase from 2019.

Differences between organizational objectives and constraints result in variation across ownership types in profit-orientation and, by extension, the tendency in engaging in activities that enhance profit. For example, government-owned hospitals (investor-owned hospitals) are most (least) likely to offer unprofitable services (Horwitz, 2005); Investor-owned hospitals are more likely to engage in upcoding to increase Medicare reimbursement and set high charges to enhance revenue (Silverman and Skinner (2004); Dafny (2005); Bai and Anderson (2015)) than non-profit hospitals. No prior research, however, has comprehensively examined hospital financial distress across ownership types.

Although the COVID-19 pandemic has affected all hospitals, lower visits have shown to affect hospitals' financial performance differently. The logit analysis in the previous section (results not reported yet) shows that hospitals' financial distress increases with outpatient surgeries, outpatient visits, and emergency room visits significantly. The drop in the visits apparently harmed patients' need for medical care, but it seems that it is not necessarily bad news regarding hospitals' financial measures. And different hospitals rely on operational indicators diffidently. For example, investor-owned hospitals rely significantly more on inpatient visits and inpatient surgeries to enhance financial performance and reduce financial distress. The COVID-19 pandemic therefore harmed investor-owned hospitals the most. As the most distressed type of hospitals by record, we estimate that the investor-owned hospitals are going to experience the hardest hit by COVID-19 in 2020.

6 Hospital Financial Distress and Service Provision

To provide insights on what real effects the estimated financial distress may have on the service provisions, and ultimately the quality of patients' care, we analyze the cross section of hospital distress probabilities in 2020 by breaking down by service code, the location of the hospital and and the ownership types.

Table 10 report the predicted share of hospitals in financial distress by service codes. Most of the hospitals in the United States are classified as general hospitals, accounting for about 78% of the total in our sample in 2020 About a quarter of the general hospitals, 24.33%, are predicted to be in financial distress in 2020.

The level of financial distress among general hospitals has not changed much during the period of 2012 to 2019, which started at 22.5% in 2012 and remained around 24.03% after 2017 Since we estimate the average financial distress in 2020 at 27.55%, the lower than the average financial distress among general hospitals suggests that it was the specialty hospitals that were hardest hit in 2020. According to the last column of Table 10, the specialty hospitals with the most volume in 2019 are Psychiatric, Acute long-term care, and Rehabilitation, which together account for 76.4% of all specialty hospitals, are estimated to experience high distress rate in 2020, 49.0%, 47.5%, and 30.53% respectively. If this elevated financial distress were to lead a reduction of the scale and the scope the service provision by these providers, or even closure of the specialty hospitals, it would affect the patients seeking these service not just during COVID-19 but long after the pandemic is over.

To put these estimates in perspective, in 2019, the specialty hospitals received 34.66 million outpatient visits. If one patient on average visits hospitals 3 times a year (CDC suggests the number of visits per person is 2.78 in 2016)[5], then the deterioration in the financial performance of the specialty hospitals would potentially affect 11.55 million patients.

The other specialty hospitals that are estimated to face higher distress in 2020 include Children's Psychiatric (60.32%), Children's orthopedic (73.20%), Children's rehabilitation (43.50%), and Intellectual disabilities (69.75%).

Table 10: PREDICTED 2020 FINANCIAL DISTRESS BY HOSPITAL SERVICE CODE

Service type	Service code	Hospitals	Predicted distressed	Total outpatient visits received in 2019
General medical and surgical	10	3,597	24.33%	590,065,101
Psychiatric	22	336	49.06%	4,653,985
Acute long-term care hospital	80	237	47.50%	1,044,597
Rehabilitation	46	191	30.53%	3,465,085
Surgical	13	76	16.63%	1,346,334
Children's general	50	46	16.53%	18,300,958
Orthopedic	47	26	13.20%	848,475
Children's psychiatric	52	13	60.32%	80,582
Heart	42	13	14.32%	832,068
Children's orthopedic	57	11	73.20%	193,893
Other specialty treatment	49	10	33.30%	443,075
Children's rehabilitation	56	8	43.50%	223,049
Alcoholism and other chemical dependency	82	8	26.35%	184,488
Obstetrics and gynecology	44	8	17.64%	1,314,318
Cancer	41	6	29.20%	867,851
Children's other specialty	59	5	7.44%	295,877
Intellectual disabilities	62	2	69.75%	0
Children's chronic disease	58	1	25.21%	33,018
Eye, ear, nose and throat	45	1	4.41%	412,346
Tuberculosis and other respiratory diseases	33	1	3.01%	112,251
Chronic disease	48	1	2.83%	7,450

NOTE. **WE NEED A DESCRIPTION OF THE VARIABLES HERE HERE**

Special hospitals have always experienced more financial distress than general ones in the past. The historical financial distress for specialty hospitals averaged 28.89% during the 2012-2019 period. It is estimated to be even worse in 2020 during COVID-19. Table 11 shows that the average **share?** financial distress for specialty hospitals in 2020 is estimated to be 40.23%, significantly higher than

[5]https://www.cdc.gov/nchs/fastats/physician-visits.htm

in the past, or the 24.23% of the general hospitals in 2020.[6]

When we breakdown the general and the specialty hospitals by the ownership types, we find that investor-owned hospitals are the main providers of specialty care, accounting for 68% of all these specialized providers. The fact that investor-owned hospitals are more prone to financial troubles leave patients with special care needs with more vulnerable both in terms of quantity and quality of the specialty services available to them. This the group of patients that would be most affected in 2020 and likely beyond, after patient seeking acute long-term care and rehabilitation, as investor-owned hospitals consist of 83% of such hospitals.

Table 11: PREDICTED 2020 FINANCIAL DISTRESS BY HOSPITAL OWNERSHIP AND SERVICE TYPES

	Service codes	**All**	**Predicted Distress**	**Nonprofit**	**Government**	**Investor**
General medical and surgical (incl. Children's general)	10 & 50	3,643	24.23%	61%	23%	16%
Specialty	All except for 10 & 50	954	40.23%	18%	15%	68%
Distressed of the largest specialty groups						
Psychiatric	22	336	49.06%	16%	35%	49%
Acute long-term care hospital	80	237	47.50%	14%	3%	83%
Rehabilitation	46	191	30.53%	15%	2%	83%

NOTE. WE NEED A DESCRIPTION NOTE HERE. ALL VARIABLES. PLS REVIEW THE RAW HEADINGS FOR MEANING AND APPEARANCE

When studying the determinants of hospital financial distress in Table 3, we showed that rural hospitals are significantly less stressed than urban hospitals. However, when we investigate the financial distress of rural and urban hospitals by the service code and by ownership type reveals a different picture. The results are presented in Table 12. First, Panel A shows that consistent with the historical tendencies, rural hospitals are estimated to be 17.16% distressed in 2020, significantly lower than Urban hospitals, about a third of which are likely to run into finacial distress, or 29.93%. Panel B and C show that 93% percent of Rural hospitals are either government or nonprofit hospitals and 99% of them are general hospitals (including Children's general hospital).

Although the predicted financial distress does not suggest that COVID-19 would have server negative effect of the rural hospitals' financial soundness per se, it does have implications on the service provisions to rural communities. Before the pandemic, rural patients would need to travel

[6] **Note here that we include the children general hospitals here as well.**

out of the area to seek specialty care as almost all rural hospitals are general hospitals. As we showed that specialty hospitals are mostly investor-owned, and such hospitals suffer the most distress in 2020, this is could lead to a reduction in services or even closures. What it means to the rural patients is that they would need to travel further or wait longer to receive specialty care now than before, especially in the types of special care such as Acute long-term care, Rehabilitation and Psychiatric.

Table 12: Rural Hospitals and Financial Distress by Service and Ownership Type

Panel A: Predicted Distress by Rural vs. Urban			
Row Labels	Financial Distress in 2020		
Urban	29.93%		
Rural	17.16%		
Panel B: Ownership Type by Rural vs. Urban			
Row Labels	Investor	Nonprofit	Government
Urban	31%	52%	17%
Rural	7%	52%	41%
Panel C: Service Type by Rural vs. Urban			
Row Labels	Total	General Hospitals	Specialty
Urban	3,741	2,795 (75%)	946 (25%)
Rural	856	848 (99%)	8 (1%)

Note. General Hospitals include Children General Hospitals.) **what does raw labels mean?** NOTE HERE

7 Conclusions

In this paper we propose to use smart-phone mobility data to predict hospitals operational indicators to evaluate their likelihood of financial distress in a standard Altman Z-score framework. We then apply the proposed predicting model to the analysis of COVID-19 impact on the financial vulnerability of US hospitals in 2020.

We show that our hospital specific mobility indicator predicts remarkably well in sample against 2018 and 2019 actual data. Consistent with bankruptcy data for 2020, we find little change in the overall probability of hospital financial distress overall, despite the major shock of the COVID-19 pandemic. Investor-owned hospitals, however, are much more affected than others. Since investor-owned hospitals are the main providers of specialty health care services such as psychiatric and acute long-term care, their increased financial distress can potentially result in long-term effects on the quality and quantity of health care provided to all communities, especially the rural communities that have already had limited access to specialty health care in the pre-pandemic period. If the increased financial distress among the investor-owned hospitals led to the reduced services or even closure of the facilities, it means that patients in the rural area would need to travel even further and/or wait longer to receive the care needed.

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A Hospital Characteristics Appendix

Appendix A shows that for-profit hospitals have less full time physicians (Figure 2), fewer full time employees (Figure 3), but a larger number of beds than government hospitals (4). In addition, the typical physician on the staff of a for-profit MHS hospital is more likely to be self-employed than other physicians. Taken together, these last two findings suggest that the financial link between the hospital and the physician may be the weakest at for-profit MHS facilities, a result that may be counter to some views of the for-profit sector.

For profit hospitals have the highest share of establishments in in distress (more than 30 percent), even though the share of government hospitals in distress is increasing (Figure 5).

Government hospitals are the most levered (Figure 6). Non profit is declining, Profit slightly increasing in 2018. Governemnt highest but stable.

But government have access to cheaper debt (Figure 7; Note here that observations reduce to 26,348). Interest expenses are increasing for profit hospitals. Stable for government hospitals. Increased in 2018 for non profit as well.

Investor hospitals are more profitable, even though profitability lower since 2016 (Figure 8 profitability NI/TA). Non profit declining profitability. Government low and increasing only slightly.

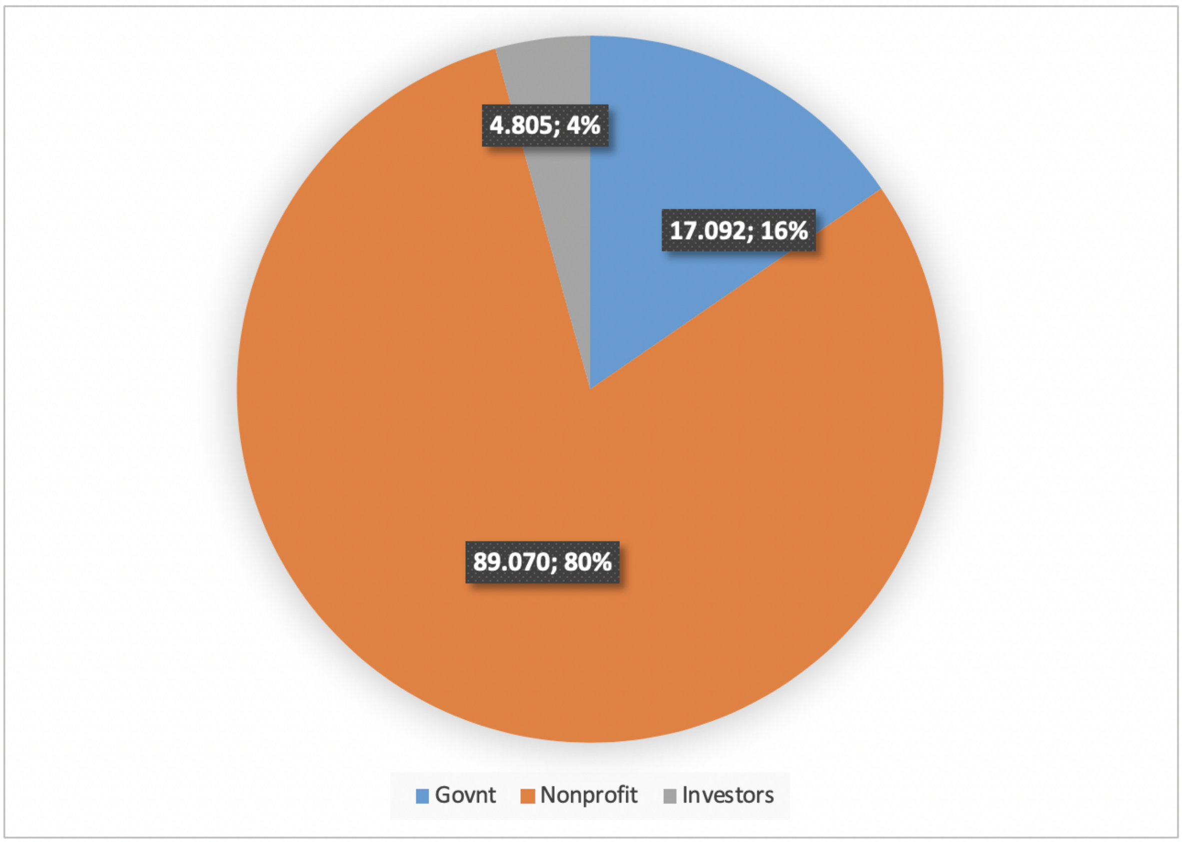

Figure 2: Full-Time Physicians by Ownership: 2011 to 2018.

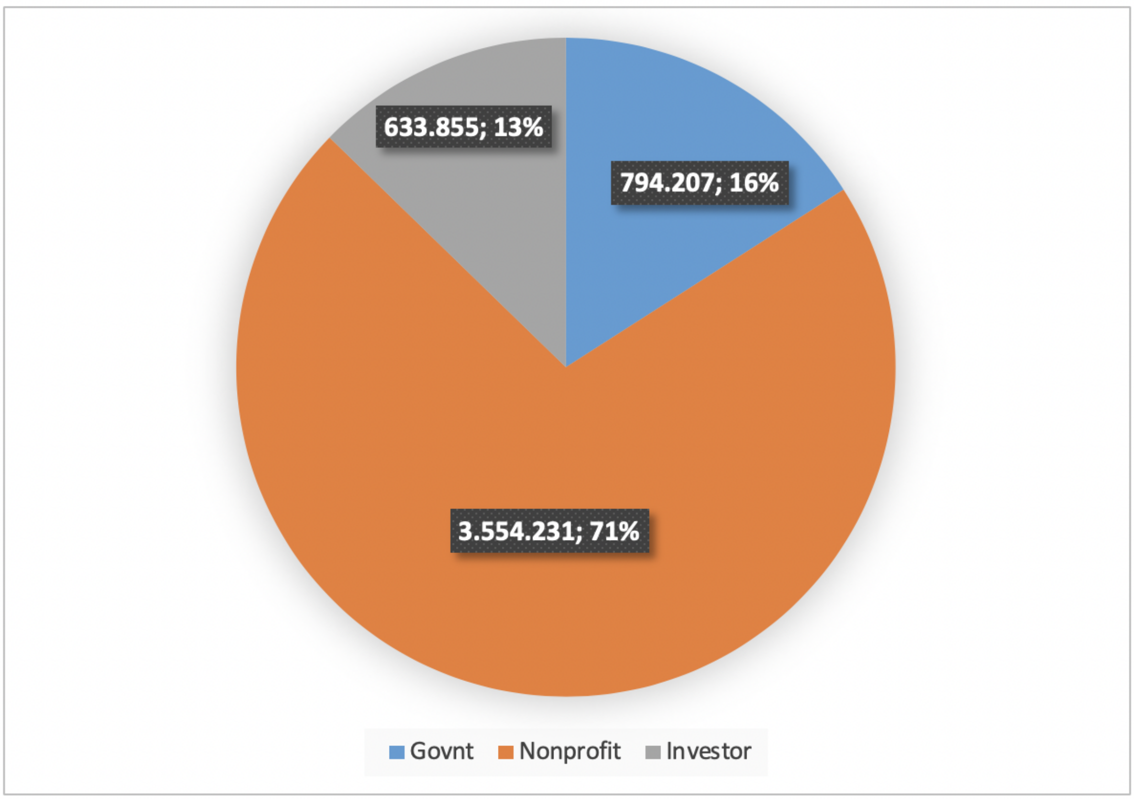

Figure 3: Full-time Employees (non-physicians) by Ownership: Annual average from 2011 to 2018.

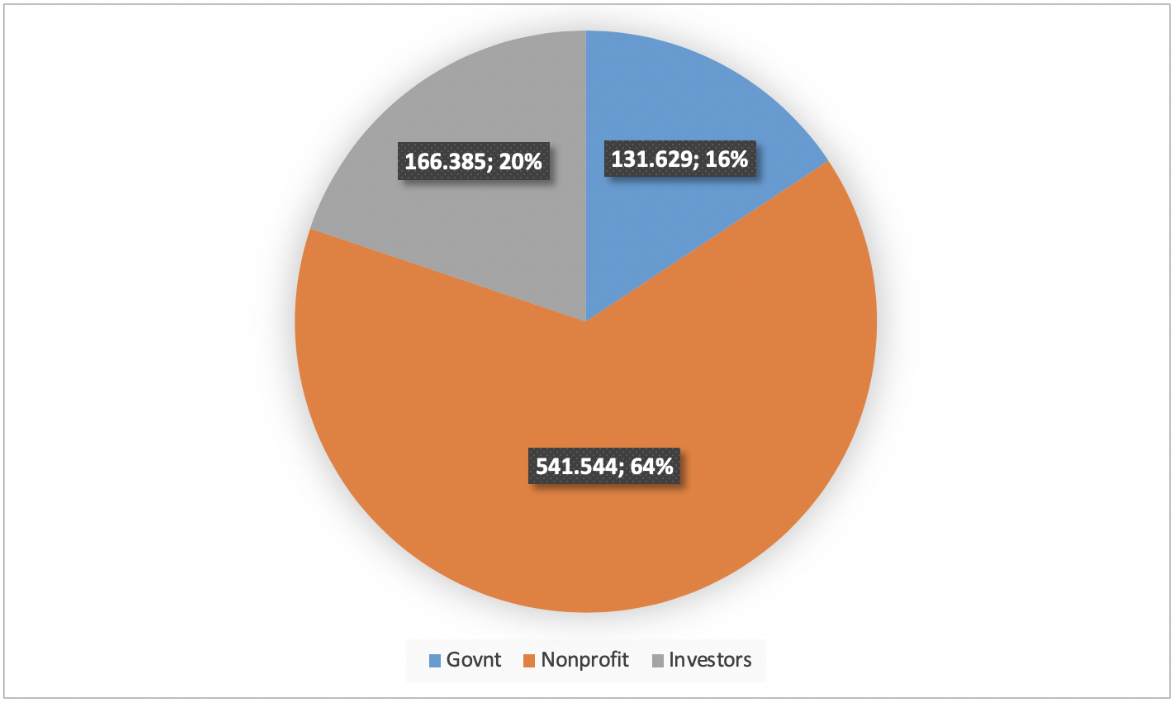

Figure 4: Hospital Beds by Ownership: Annual average from 2011 to 2018.

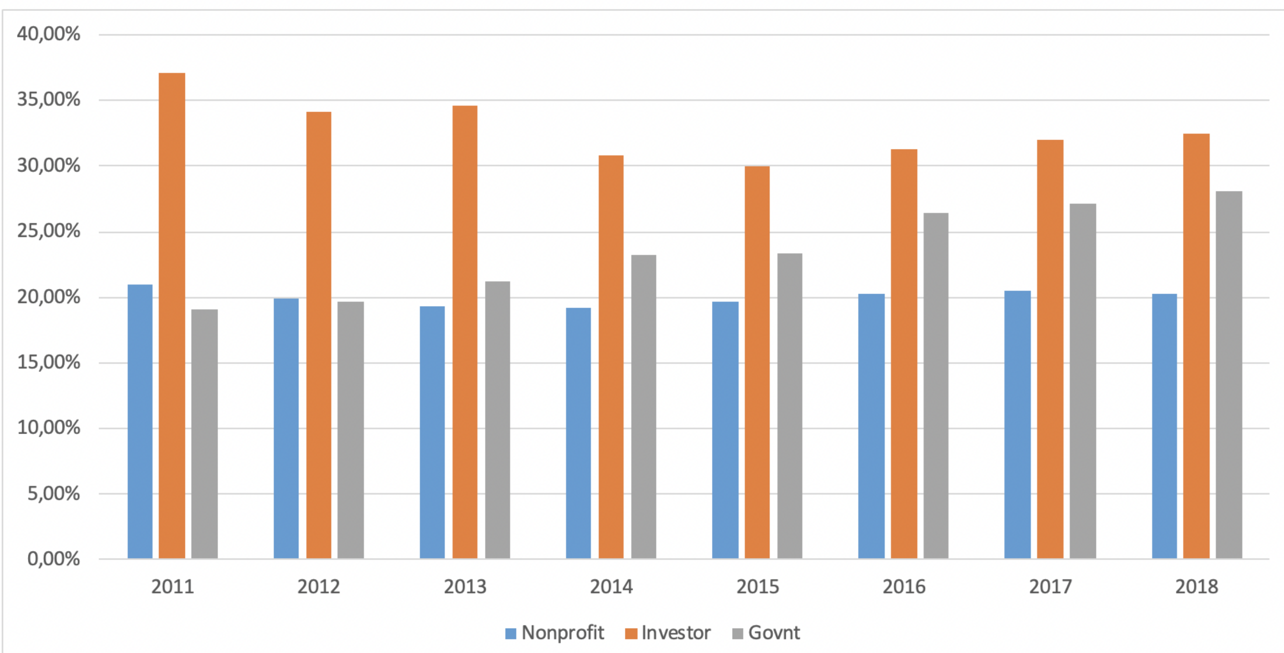

Figure 5: Percentage of Hospitals in Financial Distress.

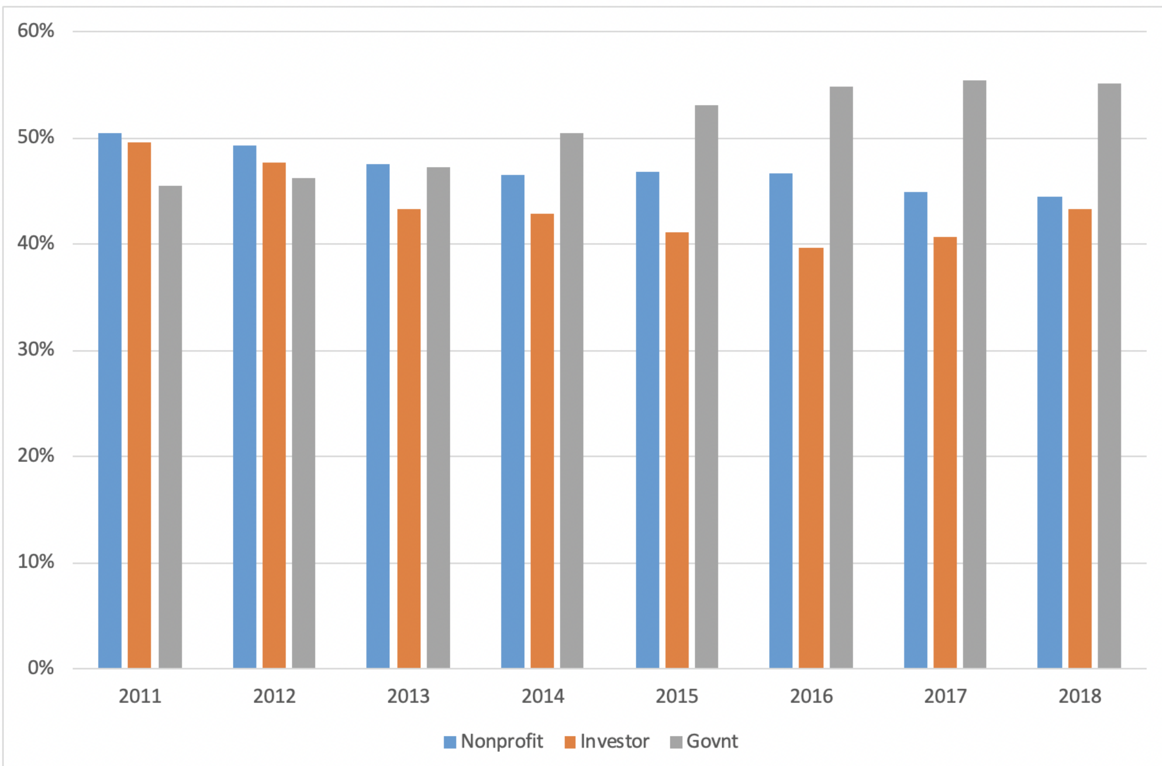

Figure 6: Leverage Ratio (TLiabilities/TAssets).

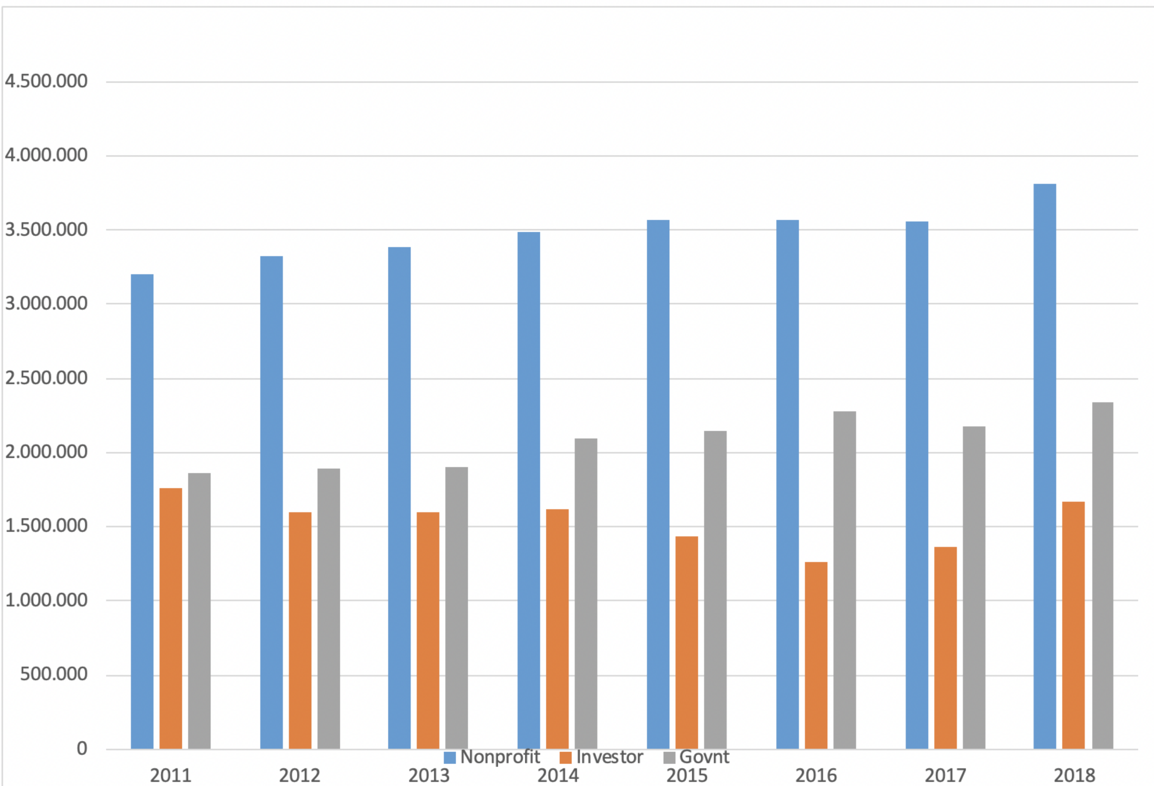

Figure 7: Average Interest Expense.