Differential Impacts of Hospital Crowding and Flu Pandemic Years on Racial Disparities in Flu Outcomes^{*}

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Introduction

Understanding and addressing the sources of racial disparities in health outcomes continue to be pressing challenges. The Covid-19 pandemic has heightened attention to these issues, as we see large disparities in mortality for Black and Latino Americans. Notably, these disparities for Covid-19 are proportionally larger than those for other infectious respiratory diseases, including mortality from flu, on average.

While there are notable disparities in death rates for influenza and pneumonia between white and Black Americans, (CDC AtlasRes) they are noticeably smaller than the disparity seen with Covid-19 deaths. CDC estimates of pneumonia and influenza mortality from the 1980s and 1990s are 1.48 times higher for Black Americans than for white. (CDC AtlasRes) More recent studies have considered variability in these disparities by U.S. region, finding disparities in pneumonia and influenza mortality up to 1.56 times higher for Black Americans than white. (Donaldson et al. 2021)

For Hispanics, distinctions with non-Hispanic whites are more difficult to identify. Some of this may be due to differences in labeling and reporting - for example, whether individuals are asked to choose Hispanic or Latino as a race, or report Hispanic/Latino separately as an ethnicity. Additionally, in some cases Hispanic patients may be incorrectly classified as 'other.' (Howland and Tsao, 2020) However, some research suggests that Hispanic patients may in fact have lower mortality rates from flu and pneumonia. The American Lung association reports mortality rates for influenza and pneumonia for Hispanics that are consistently lower than for whites from 1999 to 2013. (American Lung Association, 2015) A comparison of Hispanic and non-Hispanic whites found lower influenza and pneumonia mortality rates for Hispanic whites from 1999-2018. (Diaz-Campbell et al. 2021) The CDC notes that Hispanic patients without underlying health conditions tend to be overrepresented among hospital flu cases. (CDC 2010B)

As of March, the CDC estimated the death risk from Covid-19 was 1.9 times higher for Black and 2.3 times higher for Hispanic/Latino persons than white persons. (CDC 2021) This brings us to the question of why these disparities for Black and Latino persons are heightened in Covid mortality.

My paper considers the hypothesis that hospitals in the U.S. predictably produce wider racial disparities in mortality from infectious respiratory disease when these systems are under greater strain, particularly due to a more severe period of infectious respiratory disease.

This paper contributes to a greater understanding of the sources of racial disparities in healthcare outcomes, specifically to knowledge of if racial disparities in outcomes change in healthcare systems under strain. Understanding if strain from increased usage of healthcare systems, and resulting increases in the scarcity of resources, changes racial disparities in outcomes adds context to how we approach addressing these disparities within healthcare systems.

Past research has considered the impact of hospital crowding on patient outcomes and discharge in the UK, suggesting that hospitals with more admissions discharge patients 'quicker and sicker' with a higher likelihood of readmission. (Hoe, 2019) Research in the U.S. has found similar results, that patients have earlier discharges on high-demand days. (Sharma et al, 2008) Additional research has looked at ambulance diversion to proxy for emergency room strain, finding that largely minority serving hospitals were more likely to divert ambulances, and commented on the need for research on emergency room crowding and healthcare outcomes for minorities. (Hsia, 2012)

Recently, consideration has fallen on whether hospital policy in high strain conditions caused by Covid-19, specifically Crisis Care standards in Massachusetts, are likely to exacerbate disparities for patients of color due to higher rates of specific comorbidities among minority populations used to determine standards of care under the Crisis Care system. (Heath, 2020) By better understanding the impact of decision making in hospitals under strain, this research helps us understand how resources can be best directed to reduce racial disparities. A significant need for further research into understanding and mitigating the sources of disparities in acute respiratory infections has been highlighted in recent review literature. (Moran et al 2020) Comparing the disparities for more severe periods of respiratory infections is a key part of this work.

Research has considered the racial disparities in outcomes during flu pandemics and examined gaps in pandemic response in evaluation of programs, which has suggested that there may be larger increases in mortality for Black Americans during pandemics, and that there is particular work needed

to help support Black communities during pandemics. (Hutchins et al 2009) This is supported by recent work in Michigan, where specific work to better communicate and provide healthcare resources to Black communities narrowed the racial gap in Covid-19 cases. (Keating et al, 2020) However, the analysis of how these racial disparities change is still relatively limited in the literature. Further analysis is needed to understand these impacts in secondary and tertiary care.

For evaluation of flu pandemics, I consider the 2009 H1N1 pandemic. The 2009 H1N1 pandemic led to over 200,000 hospitalizations and 12,000 deaths in the United States. Pandemic mortality struck people under 65 years of age at a much higher rate relative to a typical flu season, where the significant majority of deaths are in patients over 65. (CDC, 2010A) In considering racial disparities from the pandemic, self-reported influenza-like illness was lower for Hispanics, and roughly the same for Black Americans as for whites, and health care seeking behavior was similar. (Dee et al 2011) However hospitalization rates were higher for minorities, (Dee et al 2011) and specifically much higher for Hispanics (CDC 2010B) and there were more deaths among Hispanic children than non-Hispanic white children. (Dee et al 2011, CDC 2010B) The CDC notes that the 2009 H1N1 pandemic was first identified in cities with high Hispanic populations, which may have driven overrepresentation in early reporting of the initial spring wave, but hospitalization disparities continued throughout the year. (CDC 2010B)

In considering healthcare outcomes, and mechanisms of disparities, it is important to consider insurance and payment. Insurance discrimination has been a subject of healthcare literature. Some research has found that Medicare patients receive lower quality care and worse risk-adjusted mortality outcomes than patients on private insurance. (Spencer, 2013) This may be in response to the fact that there are higher reimbursement rates for private insurance than for Medicare. (White and Whaley, 2019) I consider the potential for differential impacts based on insurance as well.

I consider data from California, from 2006 to 2011. Specifically, I consider hospitalized flu cases and resultant mortality. I evaluate differential changes in mortality rates for flu patients across race with increasing hospital crowding and with flu pandemics, while also considering other patient characteristics as well as time trends. In considering hospital crowding, I consider the total lengths of

stay for all patients discharged in a given quarter, over the total number of beds at that facility in that half-year times the days in that quarter. I consider the 2009 H1N1 flu pandemic specifically. I control for patient health risks to mortality with the age-adjusted Charlson Comorbidity Index. I also consider differential effects of payer and hospital strain interactions, in order to consider differential effects for specifically low-income patients and potential for insurance discrimination.

In my findings, I confirm both the significance of the 2009 H1N1 flu pandemic to flu hospitalization and mortality, as well as validating the use of the age-adjusted Charlson to predict mortality for flu patients. While the results for racial disparities are not so clear cut, there are some suggestive results for Hispanic patients, pointing to higher mortality for male patients and lower mortality for female patients in average times, but higher hospital occupancy drives these in opposite directions. These point to a need for further study in a larger sample. In terms of pandemic years, the most striking result is the higher rates of mortality for patients who are expected to 'self-pay' - that is, who are without insurance. This is particularly notable as this effect does not appear for patients without insurance outside of pandemic years. These results suggest these questions are ripe for further study.

Data

Hospital patient data was made available via the National Bureau of Economic Research (NBER) from the Healthcare Cost and Utilization Project (HCUP), specifically the state inpatient databases, after a successful data reuse application. This dataset provides deidentified patient characteristics, diagnoses, procedures, and outcomes. Using California data from 2006-2011, I pulled data on diagnoses, procedures, age, sex, race, expected payer for care, length of stay, quarter of the year when the patient was discharged, and whether the patient died in the hospital or was discharged. Race is labeled as classified in the data. Cases with flu diagnoses were isolated from ICD 9 codes 487-488.89.

Hospital bed counts were made available from the California Office of Statewide Health Planning and Development (OSHPD), with thanks to Jasmine Neeley. Hospital information was available twice yearly. Hospitals were matched by the HCUP dshospid and the last 6 digits of the

oshpdid. Matching by time matched quarters in each half of the year with the hospital bed count. Hospital crowding is calculated by summing the length of stay in each quarter and dividing that by the number of days in the quarter multiplied by the bed count in that hospital in that quarter. The mean occupancy ratio is 0.71 and the standard deviation of occupancy ratios is 0.21.

The age-adjusted Charlson comorbidity index is used to predict mortality risk, and is commonly used in assessing mortality risk and widely validated, with comparable efficacy to other comorbidity classification methods for chronic obstructive pulmonary disease. (Austin et al, 2012) It has been used for flu patients specifically (Gutiérrez-González et al 2019) and chronic obstructive pulmonary disease (Austin et al, 2012) and patients with respiratory infections generally. (Setter et al, 2019) The Charlson comorbidity index calculates a score for each patient, adding points for specific diagnoses - the higher the score, the higher the risk. The age adjustment adds a point for each decade over 40. (Charlson et al, 1994) The icd R package charlson function was used to calculate patient Charlson comorbidity indices from the HCUP data, using Quan scoring weights. (Wasey, 2018) The age adjustment was calculated with my own R code.

HCUP Data Summary

In California from 2005-2011, there are 27.9 million entries for hospital patients; 13.1 million of those are for white patients, while 7.8 million are for Hispanic patients, 2.0 million are for Black patients, and 2.0 million are for Asian American and Pacific Islander (AAPI) patients. There are 49.6 thousand total hospitalized, recorded flu cases in this period, with 19.6 thousand flu cases among white patients, 15.8 thousand flu cases among Hispanic patients, 3.8 thousand flu cases among Black patients, and 3.4 thousand flu cases among AAPI patients. There are 1.3 thousand flu deaths, with 632 flu deaths among white patients, 407 flu deaths among Hispanic patients, 80 flu deaths among Black patients and 94 flu deaths among AAPI patients. Race labels also include, Native American, and 'Other', these are still included as dummies in regressions but are not reported as the Native American sample is small, with only 23 thousand total entries, and while all these populations are heterogeneous, the difficulty of assessing the nature of the heterogeneity in the 'Other' population makes it difficult to draw conclusions from any results. The AAPI population in California is also noted as being especially

heterogeneous, and these results are also not reported in further tables though they are included in the regressions.

For comparison, the 2010 California census has 57.59% of the population as 'white alone', over 21 million, with 'persons of Hispanic or Latino origin' at 37.62%, 14 million, 'Black or African American alone' at 6.17% of the population, 2 million, Asian alone at 13.05% of the population, nearly 5 million, Native Hawaiian and Other Pacific native alone at 0.39% of the population. (Census, 2010) Some discrepancies in proportions may be due to differences in labeling racial and ethnic categories.

HCUP Data Trends

The following are graphical illustrations of the HCUP data to provide a visual for the trends in the data and a broader framework for the results.

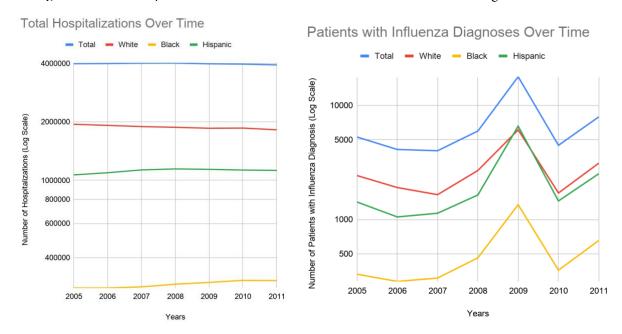


Figure 1: Total Hospitalizations over Time and Patients with Influenza Diagnoses Over Time

Note: Both sets presented on a log scale. Note that total hospitalizations over time is largely flat, while the 2009 flu pandemic is clearly identifiable in the patients with influenza diagnoses.

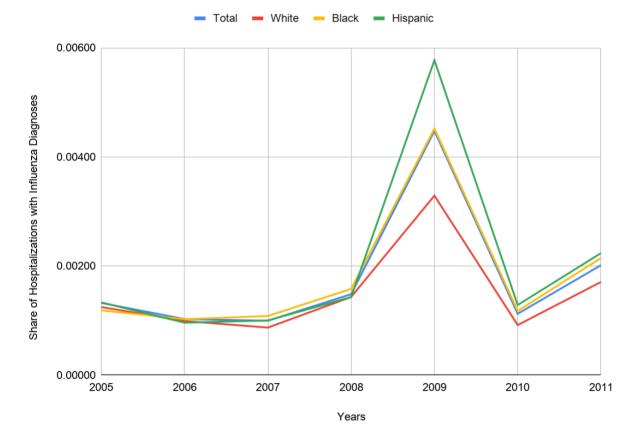


Figure 2: Share of Hospitalizations with Influenza Diagnoses

Note: Share is calculated by taking the total number of influenza diagnoses among hospitalized patients in that year for a given race and dividing it by the total number of hospitalized patients of that race. The 2009 pandemic is clearly identifiable with a comparatively higher share of patients with flu.

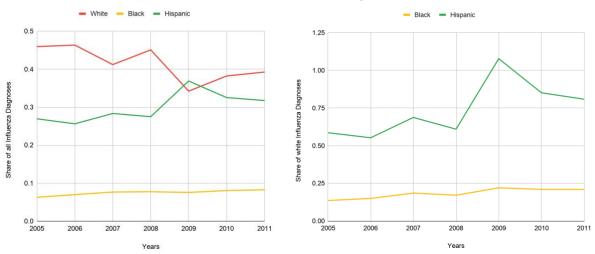


Figure 3: Share of Influenza Diagnoses

White, Black, and Hispanic Influenza Diagnoses as a share of all Influenza Diagnoses

Black and Hispanic Flu Diagnoses as a share of white Influenza Diagnoses

Note: Share is calculated by taking the total number of influenza diagnoses in that year for a given race and dividing it by the total number of influenza diagnoses in that year or the total number of influenza diagnoses in white patients in that year. Note that 2009 is the one time the share of Hispanic diagnosis overtakes the white share. The Hispanic line has a much larger 'jump' in share in 2009 than the Black line, which remains comparatively flat.

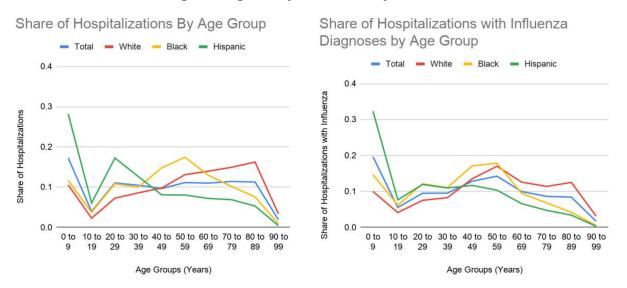


Figure 4: Age Group Shares of Hospitalizations

Note: Share is calculated by taking the total number of influenza diagnoses in that age group for a given race and dividing it by the total number of influenza diagnoses of that race.

Across these figures, when considering year-to-year changes, the impact of the 2009 H1N1 influenza pandemic is clear, whether in absolute numbers of flu patients (Figure 1 panel B) or in share of hospitalizations (Figure 2), though the increase does not make a dent in the overall hospitalization numbers (Figure 1 panel A). Hispanic patients appear to have been more substantially impacted by the 2009 pandemic than white or Black patients, (Figure 3) which matches with prior research. (CDC 2010B)

When considering age groups, both across all hospital cases and flu patients, there are more white patients in older age groups. (Figure 4) Flu hospitalizations have a peak around the 50-59 age group, though that peak appears to be shifted somewhat earlier for the Hispanic patients. This is not surprising, as the median age for Hispanics in the U.S. is about a decade younger than the non-Hispanic white population. (CDC 2010B)

Methods

The primary effect I am estimating is the effect of pandemic years and hospital occupancy on flu patient mortality for Black and Hispanic patients as compared to white patients, in order to consider if hospital crowding or pandemics contribute to or exacerbate flu mortality disparities.

Specifications

$$M = \alpha + \beta_1 * F + \beta_2 * F * R + \beta_3 * R + \beta_4 * T^2 + \beta_5 * G + \beta_6 * S + \beta_7 * P + \beta_8 * C + \varepsilon$$
 [Equation 1]

Here M is a binary for whether or not a patient diagnosed with flu dies in the hospital during flu season, F is either pandemic year/post-pandemic year and/or a hospital occupancy measure, R is race, T is time in years starting at first year of data, G is age, S is sex, P is expected payer (e.g., Medicare, Medicaid, Private Insurance, Self-Pay, etc.), and C is age-adjusted Charlson Index. Post-pandemic year is included to account for the fact that the 2009 H1N1 strain was still circulating as well as changes hospitals may have made in response to the pandemic to better prepare for flu pandemics. Further, I include a flu severity, race, and sex interaction term, to account for the possibility that disparities affect Black men and Black women differently, as has been suggested by some prior health disparities research. (Schulman et al. 1999) Additional covariates include hospital fixed effects. I use logistic

regression for this analysis, as the dependent variable – mortality - is binary. I additionally consider a similar model, examining the role of expected payer in place of race in order to consider the possibility of insurance discrimination.

Results

Initial Visualizations

The following are initial visualizations of the data regarding hospital mortality for flu patients.

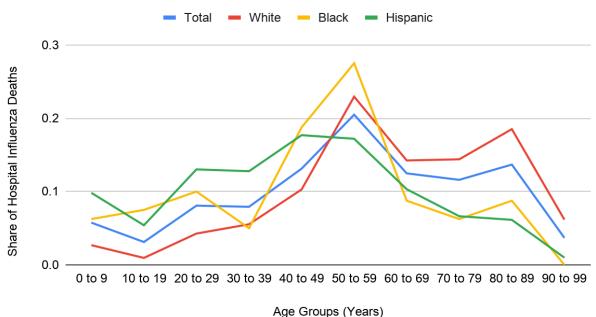


Figure 5: Share of Hospital Influenza Deaths by Age Group.

Note: Share calculated by taking the count of flu deaths in that age group and race over the total count of flu deaths in that race.

As would be expected from the higher share of older white patients from Figure 4, there is a higher share of flu deaths among older patients. The peak flu patient deaths appear to be in the 50 - 59 age group, as was the middle peak for flu hospitalizations. The peak for flu hospitalizations for very young patients does not translate to a similar mortality peak. There also appears to be an additional, smaller peak in the 80-89 age group. As was the case for hospitalizations, the peak for Hispanic patient mortality appears to be shifted to a slightly earlier age group, with the highest share in the 40-49 age group, which tracks with the younger median age.

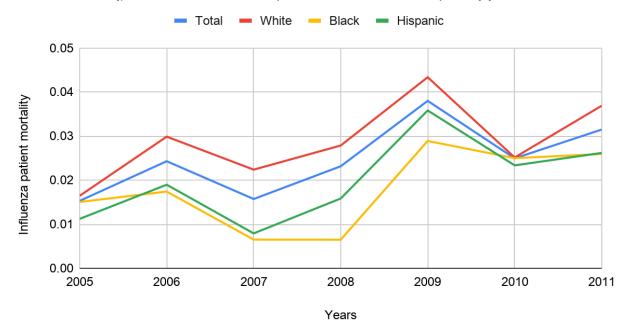


Figure 6: Share of Influenza patients who die in the hospital by year

Note: Share is calculated by taking the number of flu deaths of that race in that year over the number of flu diagnoses of that race in that year. Note that the 2009 flu pandemic peak is clearly visible.

While the 2009 flu pandemic is visible here, the jump in share of deaths is not as dramatic as in hospitalizations (Figure 2). White patients appear to consistently have the highest share of deaths. There appears to have been a steeper impact of the 2009 H1N1 pandemic on mortality rates for Black and Hispanic patients compared to the overall change.

Regression Results

Initial checks were run examining the relationships surrounding the age-adjusted Charlson. First, I consider the relationship between race and the age-adjusted Charlson, in order to examine whether Black and Hispanic patients were more or less likely to come into the hospital with a flu case with a higher age-adjusted Charlson score.

I able 1: Linear Regression of Age Ad	justed Charlson for Flu Patients on Race
Black	-0.6847****
	(0.05058)
Hispanic	-1.5084****
1	(0.03034)

Table

Note: Standard Errors in parentheses. Left out category for race is white. Other races included in regressions as coded in the data but not reported here. No other controls included. Significance codes are as follows: **** indicates p-values between 0.001 and 0, *** indicates p-values between 0.01 and 0.001, ** indicates p-values between 0.01 and 0.05, * indicates p-values between 0.05 and 0.1, . indicates p-values between 0.1 and 0.2, no marking indicates p-values between 0.2 and 1.

Absent other controls, these results (Table 1) suggest that Black and Hispanic patients with flu are more likely to enter the hospital with a lower age-adjusted Charlson score, and therefore presumed to have a lower risk of death. In the Hispanic case, this tracks with prior literature that Hispanic patients without underlying health conditions are overrepresented among hospitalized flu patients. (CDC 2010B) Further examination of these results may include examining this analysis with more controls, such as controlling for expected payer, and looking at the Charlson alone, to see how much these results are being driven by different age distributions among hospital inpatients. Additional examinations may include examining diagnoses related to severe flu cases, such as pneumonia, to examine whether Black and Hispanic flu patients are entering the hospital with higher baseline health but more severe flu cases.

Further examination in this paper includes an initial test of flu mortality on race and ageadjusted Charlson, to see if, absent other controls, the age-adjusted Charlson was more predictive of mortality for Black and Hispanic patients than white patients.

l al	Sie 2: Logistic Regression of Flu Mortality of	Race and Age Adjusted Charts
	Black	-0.3756*
		(0.22299)
	Hispanic	0.1226
		(0.1129)
	Age Adjusted Charlson	0.2185****
		(0.01442)
	Black*Age Adjusted Charlson	0.0262
		(0.0408)
	Hispanic*Age Adjusted Charlson	0.0145
		(0.0227)

Table 2: Logistic Regression of Flu Mortality on Race and Age Adjusted Charlson

Note: Standard Errors in parentheses. Left out category for race is white. Other races included in regressions as coded in the data but not reported here. No other controls included. Significance codes are as follows: **** indicates p-values between 0.001 and 0, *** indicates p-values between 0.01 and 0.05, * indicates p-values between 0.05 and 0.1, . indicates p-values between 0.1 and 0.2, no marking indicates p-values between 0.2 and 1.

No strong relationship emerges in the interactions between race and the age-adjusted Charlson (Table 2), apart from the strong relationship between age-adjusted Charlson and flu patient mortality, with a one-point increase in age-adjusted Charlson leading to a risk of death that is 1.24 times higher. Even considering the lower bound of the 95% confidence interval, a one-point increase still carries a risk of death that is 1.21 times higher. This relationship remains largely consistent and highly significant throughout further regressions, validating the use of the age-adjusted Charlson in predicting mortality for flu patients in a hospital setting.

After these initial analyses, the following analysis delves into examining the relationship between mortality, race, flu severity and hospital crowding. The following analysis, considers the mortality of flu patients regressed on race and the hospital occupancy ratio in that quarter.

I able 3: Logistic Regression of Flu Mortality on Race and Hospital Occupancy Ratio.						
Black	-0.0579	0.0378	-0.0174	-0.0186	-0.0110	-0.7063
	(0.5131)	(0.4873)	(0.4960)	(0.4951)	(0.5368)	(0.6002)
Hispanic	-0.3122	0.0489	-0.0508	-0.0522	0.1945	0.6737*
	(0.2506)	(0.2337)	(0.2383)	(0.2382)	(0.2804)	(0.3883)
Occupancy Ratio	-0.1330	-0.0552	-0.0522	-0.0552	0.0625	0.3238
1 7	(0.1971)	(0.1888)	(0.1901)	(0.1904)	(0.8828)	(0.4659)
Black*Occupancy Ratio	-0.5132	-0.4212	-0.4542	-0.4468	-0.4938	0.3320
1 2	(0.7094)	(0.6708)	(0.6837)	(0.6824)	(0.7298)	(0.7581)
Hispanic*Occupancy Ratio	0.1472	0.1774	0.1795	0.1845	-0.2145	-0.8883*
1 1 5	(0.3443)	(0.3180)	(0.3238)	(0.3236)	(0.3770)	(0.5290)
Black*Female	. ,	. ,	. ,	. ,	. ,	1.5620*
						(0.9397)
Hispanic*Female						-0.9821*
1						(0.5265)
Black*Female*Occupancy Ratio						-1.9660
in the start from from the start of the star						(1.2920)
Hispanic*Female*Occupancy Ratio						1.3850*
						(0.7250)
Age Adjusted Charlson Control		Х	Х	Х	Х	x
Expected Payer Control			Х	Х	Х	х
Age Control				Х	Х	х
Sex Control				Х	Х	х
Time ² Control					Х	х
Hospital Control					х	Х

Table 3: Logistic Regression	of Flu Mortality	on Race and Hos	oital Occupancy Ratio.
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Note: Standard Errors in Parentheses. Left out category for race is white. Other races included in the regression as coded in the data but not reported here. Controls for age adjusted Charlson, expected payer, age, sex, time from 2005, and hospital identifier included as noted in the table. Significance codes are as follows: **** indicates p-values between 0.001 and 0, *** indicates p-values between 0.01 and 0.001, ** indicates p-values between 0.01 and 0.05, * indicates p-values between 0.05 and 0.1, . indicates p-values between 0.1 and 0.2, no marking indicates p-values between 0.2 and 1. Hospital Occupancy ratio is calculated as the sum of patient length of stays ending in that quarter over the number of beds in that hospital times the number of days in the quarter.

Here, some weakly significant and potentially interesting results emerge. Consider the full specification, containing all controls and interactions (Table 3, coefficient column 6). The positive coefficient for Hispanic patients is significant at the 0.1 level, suggesting that Hispanic flu patients, given the full set of controls, are 1.96 times more likely to die in the hospital than comparable white patients. This would appear to contradict the prior research on lower flu and pneumonia mortality for Hispanics, (American Lung Association, 2015) however, this prior research was not conditional on hospitalization. Additionally, the coefficient on female Hispanic flu patients is negative, and also significant at the 0.1 level, suggesting that female Hispanic flu patients are only 0.37 times as likely to

die. Therefore, the positive Hispanic coefficient would appear to be driven by male Hispanic flu patients being more likely to die. This apparent lower risk of death for female Hispanic flu patients may contribute to the overall lower influenza and pneumonia mortality rates among Hispanics. Unexpectedly, when considering the relationships with hospital occupancy, the opposite relationship appears. The coefficient on the Hispanic*Occupancy ratio interaction is negative and also significant at the 0.1 level, while the coefficient on the Hispanic*Female*Occupancy ratio is positive and significant at the 0.1 level. This suggests that increased hospital crowding increases mortality for female Hispanic flu patients, while it decreases mortality for male Hispanic flu patients. Considering the standard deviation of occupancy ratios is 0.2093, this suggests that a one standard deviation increase in hospital crowding means that the mortality risk for male Hispanic flu patients is 0.83 times lower, while for female Hispanic flu patients it is 1.34 times higher. As these coefficients are only weakly significant, and the signs are not consistent throughout the different specifications, further examination is necessary to determine if these initial results are truly representative, such as including additional years and states.

When considering the results for Black flu patients, no significant results - even weakly significant results - emerge until the full specification, where we see a weakly significant but positive coefficient on Black female flu patients. This coefficient suggests that mortality for Black female flu patients is 4.77 times higher, without higher occupancy. As the coefficient on Black flu patient mortality overall is not significant in any specification, and is frequently negative, this is unexpected. However, the upper bound of the 95% confidence interval on the Black coefficient is 0.47, which would suggest Black flu patients have mortality risk that is 1.6 times higher, so we cannot entirely rule out significant results for Black patients. For the coefficient on the interaction between the occupancy ratio and Black patients, the upper bound of the 95% confidence interval is 1.82, while the lower bound is -1.15, so we cannot rule out positive or negative results. The lower bound of the 95% confidence interval is 1.82, while the lower bound is -1.15, so we cannot rule out positive or negative results. The lower bound of the 95% confidence interval is 1.82, while the lower bound is -1.15, so we cannot rule out positive or negative results. The lower bound of the 95% confidence interval for the coefficient on interactions between hospital occupancy and Black female patients is -4.50, and the upper bound is 0.56, so we cannot rule out effects in either direction, but if

there are any effects, negative effects seem noticeably more likely. As the coefficient on Black female flu patients is a weakly significant result, further examination is necessary to determine if these initial results are truly representative, such as including additional years and states. Such an expansion may also point to new results for the other coefficients.

Also of interest is the lack of significance of coefficients for hospital occupancy. While effects in either direction cannot be ruled out, as the upper bound of the 95% confidence interval is 1.24 and the lower bound is -0.59, it does not immediately suggest a strong positive relationship. This may suggest that hospital crowding has no or only a small role in flu patient mortality, or that this ratio over a quarter is not an effective measure of hospital crowding, or that hospital crowding should be considered in terms of flu patients and therefore likely associated resources (e.g., ventilators) being taken up, rather than total patient count and total occupancy. These are all opportunities for further investigation.

In the following analysis, I consider the impact of the flu pandemic of 2009 and the postpandemic years.

Table 4: Logistic Regression of Flu Mortality on Race and Pandemic and Post-Pandemic Years					
Black	-0.9093**	-0.6605	-0.7020*	-0.7801**	-0.5101
	(0.3675)	(0.4097)	(0.3696)	(0.3775)	(0.4828)
Hispanic	-0.5053***	0.1649	-0.0982	-0.1534	-0.1699
	(0.1780)	(0.2020)	(0.1822)	(0.1877)	(0.2616)
Pandemic Year	0.4519****	0.7077****	0.6983****	0.5889****	0.7108****
	(0.1122)	(0.1141)	(0.1147)	(0.1586)	(0.1979)
Post-Pandemic Year	0.1657.	0.2072*	0.2060*	-0.0207	0.1861
	(0.1231)	(0.1243)	(0.1245)	(0.2961)	(0.3204)
Black* Pandemic Year	0.4881	0.3721	0.3488	0.4151	0.0481
	(0.4076)	(0.4097)	(0.4099)	(0.4156)	(0.5543)
Hispanic* Pandemic Year	0.3179.	0.1649	0.1553	0.1968	0.2876
-	(0.2004)	(0.2020)	(0.2022)	(0.2062)	(0.2904)
Black*Post Pandemic Year	0.6381.	0.5215	0.5134	0.5713.	0.0208
	(0.4274)	(0.4299)	(0.4301)	(0.4354)	(0.5895)
Hispanic*Post Pandemic Year	0.2397	0.1723	0.1728	0.1732	0.0289
	(0.2206)	(0.2222)	(0.2224)	(0.2264)	(0.3165)
Black*Female					-0.6045
					(0.7678)
Hispanic*Female					0.0496
					(0.3646)
Black*Female*Pandemic Year					0.7709
					(0.8505)
Hispanic*Female*Pandemic Year					-0.1986
					(0.4108)
Black*Female*Post Pandemic Year					1.1430.
					(0.8914)
Hispanic*Female*Post Pandemic Year					0.3022
					(0.4534)
Age Adjusted Charlson Control		Х	Х	Х	Х
Expected Payer Control			X	X	X
Age Control			X	Х	Х
Sex Control			Х	Х	Х
Time ² Control				Х	X
Hospital Control				X	X

Note: Standard Errors in parentheses. Left out category for race is white. Other races included in the regression as coded in the data but not reported here. Controls for age adjusted Charlson, expected payer, age, sex, time from 2005, and hospital identifier included as noted in the table. Significance codes are as follows: **** indicates p-values between 0.001 and 0, *** indicates p-values between 0.01 and 0.001, ** indicates p-values between 0.01 and 0.05, * indicates p-values between 0.05 and 0.1, . indicates p-values between 0.1 and 0.2, no marking indicates p-values between 0.2 and 1. Out of a range of 2005-2011, the flu pandemic year is 2009, and post pandemic years are 2010 and 2011.

The impact of the 2009 flu pandemic is immediately clear in this analysis, (Table 4) with a consistently significant positive coefficient across specifications, suggesting, per the final specification, that flu patients were about twice as likely to die in the 2009 pandemic. Post-pandemic years do not

stand out in their effects. Interestingly, the effects for Hispanic patients, and specifically Hispanic female patients, do not persist in this specification. There is a positive coefficient on Black female patients interacted with post-pandemic years that approaches significance (significant at 0.2 level). This may suggest that the positive coefficient on Black female patients in the earlier specification (Table 3) is driven by impacts in 2010 and 2011 within this dataset. There do not appear to be a significant relationship with the interaction between Hispanic patients and the 2009 pandemic, which is surprising given the prior research on the disproportionate impact of the 2009 pandemic on Hispanic populations and particularly Hispanic children. (Dee et al 2011, CDC 2010B)

The following specification includes both hospital occupancy and pandemic/post-pandemic years as potentially having a differential impact based on race.

Post Pandemic years, and Occupancy Ratio						
Black	-0.3841	-0.7196				
	(0.6281)	(0.7319)				
Hispanic	-0.0211	0.4339				
	(0.3279)	(0.4584)				
Pandemic Year	0.5903****	0.7058****				
	(0.1587)	(0.1980)				
Post Pandemic Year	-0.0206	0.1800				
	(0.2963)	(0.3205)				
Black*Pandemic Year	0.4318	0.0311				
	(0.4173)	(0.5536)				
Hispanic*Pandemic Year	0.1956	0.2890				
-	(0.2062)	(0.2905)				
Black*Post Pandemic Year	0.5857.	0.0011				
	(0.4367)	(0.5896)				
Hispanic*Post Pandemic Year	0.1714	0.0280				
1	(0.2265)	(0.3165)				
Occupancy Ratio	0.2076	0.4273				
1 5	(0.4533)	(0.4919)				
Black*Occupancy Ratio	-0.5749	0.3063				
1 5	(0.7381)	(0.7736)				
Hispanic*Occupancy Ratio	-0.1853	-0.8555.				
1 1 5	(0.3777)	(0.5321)				
Black*Female		0.8472				
		(1.1580)				
Hispanic*Female		-0.9010.				
1		(0.6223)				
Black*Female*Pandemic Year		0.8905				
		(0.8573)				
Hispanic*Female*Pandemic Year		-0.2005				
1		(0.4109)				
Black*Female*Post Pandemic Year		1.2400.				
		(0.8977)				
Hispanic*Female*Post Pandemic Year		0.2971				
1		(0.4535)				
Black*Female*Occupancy Ratio		-2.2080*				
1 7		(1.327)				
Hispanic*Female*Occupancy Ratio		1.3560*				
1 1 2		(0.7231)				
Age Adjusted Charlson Control	Х	x				
Expected Payer Control	Х	Х				
Age Control	Х	х				
Sex Control	Х	х				
Time ² Control	Х	Х				
Hospital Control	Х	Х				

Table 5: Logistic Regression of Flu Mortality on Race, Pandemic and Post Pandemic years, and Occupancy Ratio

Note: Left out category is white. Other races included as coded in the data but not reported. Controls for age adjusted Charlson, expected payer, age, sex, time from 2005, and hospital identifier included as noted in the table. Significance codes are as follows: **** indicates p-values between 0.001 and 0, *** indicates p-values between 0.01 and 0.001, ** indicates p-values between 0.01 and 0.05, * indicates p-values between 0.05 and 0.1, . indicates p-values between 0.1 and 0.2, no marking indicates p-values between 0.2 and 1. Hospital Occupancy ratio is calculated as the sum of patient length of stays ending in that quarter over the number of beds in that hospital times the number of days in the quarter. Out of a range of 2005-2011, the flu pandemic year is 2009, and post pandemic years are 2010 and 2011.

Once again, the impact of the 2009 pandemic is clear and significant, with flu patients in 2009 being about twice as likely to die. This indicates that the impacts of the 2009 pandemic on mortality for flu patients are not driven largely by impacts on hospital occupancy. This makes sense, as the mean hospital occupancy ratio in 2009 was 0.71, nearly identical to the average hospital occupancy ratio for 2006-2011. However, as in the previous cases, neither post-pandemic years nor hospital occupancy has a strong impact.

In the final specification, in the last column of Table 5, we largely see similar patterns as in the prior two individual specifications of pandemic/post-pandemic years and hospital occupancy. Looking at Hispanic patients, similar patterns emerge, though significance is reduced. There is still a positive coefficient on flu patients, though it is no longer even marginally significant. For female Hispanic patients, there is a negative coefficient, as in the occupancy specification, though it is only significant at the 0.2 level, and therefore only approaching marginal significance. As in the pandemic years, respectively, show no significance. However, the interactions with occupancy ratios have more potential. As in the initial occupancy regression, the interaction for Hispanic patients and occupancy has a negative coefficient, although in this case it is only significant at the 0.2 level, and therefore only approaching for Hispanic patients and occupancy has a positive coefficient, although in this case it is only significant at the 0.2 level, and therefore only approaching the interaction for Hispanic patients and occupancy has a positive coefficient, although in this case it is only significant at the 0.2 level, and therefore only approaching marginal significance. The interaction for Hispanic female patients and occupancy has a positive coefficient, as before, significant at 0.1. Similarly, the coefficient on the interaction between

Black female patients and occupancy had a negative coefficient. These results, particularly with their occurrence in multiple specifications, suggest the need for further research.

In the following specification, I consider the relationship between the expected payer and both pandemic years and occupancy, to consider whether, for example, Medicaid patients are especially worse off in pandemic years or more crowded hospitals.

Post Pandemic Years.					
Medicaid	0.9008***	0.0952	0.5719.		
	(0.3318)	(0.2172)	(0.1335)		
Private Insurance	0.0922	-0.3003.	-0.3940		
	(2.8790)	(0.2049)	(0.3359)		
Self-Pay	0.8890.	-1.1410.	-0.7279		
	(0.6041)	(0.7224)	(0.9247)		
Occupancy Ratio	0.1045		0.2534		
	(0.4424)		(0.4697)		
Medicaid*Occupancy Ratio	-0.7298.		-0.6918.		
1	(0.4581)		(0.4593)		
Private Insurance*Occupancy Ratio	0.1368		0.1174		
1 7	(0.3824)		(0.3765)		
Self-Pay*Occupancy Ratio	-0.5560		-0.6036		
	(0.8465)		(0.8372)		
Pandemic Year		0.3514**	0.3508**		
		(0.1674)	(0.1674)		
Post Pandemic Year		-0.1511**	-0.1516		
		(0.3023)	(0.3027)		
Medicaid*Pandemic Year		0.3516.	0.3496.		
		(0.2334)	(0.2337)		
Private Insurance*Pandemic Year		0.6627***	0.6661***		
		(0.2302)	(0.2303)		
Self-Pay*Pandemic Year		1.9800***	1.9820***		
5		(0.7434)	(0.7435)		
Medicaid*Post Pandemic Year		0.4057.	0.4084.		
		(0.2497)	(0.2500)		
Private Insurance*Post Pandemic Year		0.4876*	0.4949**		
		(0.2507)	(0.2508)		
Self-Pay*Post Pandemic Year		1.5670**	1.5610**		
		(0.7766)	(0.7769)		
Time ² Control	Х	X	X		
Age Adjusted Charlson Control	Х	Х	Х		
Age Control	X	X	X		
Sex Control	X	X	X		
Race Control	X	Х	Х		
Hospital Control	X	X	X		

Table 6: Logistic Regression of Mortality on Payer, Occupancy Ratio, Pandemic and

Note: Left out category is Medicare. 'Other' category for expected payer included as coded in the data but not reported. Controls for age adjusted Charlson, Race, age, sex, time from 2005, and hospital identifier included as noted in the table. Significance codes are as follows: **** indicates p-values between 0.001 and 0, *** indicates p-values between 0.01 and 0.001, ** indicates p-values between 0.01 and 0.05, * indicates p-values between 0.05 and 0.1, . indicates p-values between 0.1 and 0.2, no marking indicates p-values between 0.2 and 1. Hospital Occupancy ratio is calculated as the sum of patient length of stays ending in that quarter over the number of beds in that hospital times the number of days in the quarter. Out of a range of 2005-2011, the flu pandemic year is 2009, and post-pandemic years are 2010 and 2011. When considering only occupancy (Table 6, first column), Medicaid stands out with its positive coefficient, significant at the 0.1 level. This suggests, in isolation, that Medicaid patients are 2.46 more likely to die than Medicare patients, controlling for other factors (including age and age-adjusted Charlson, to account for other health factors). However, this magnitude and significance disappears in the pandemic year specification, and is smaller and only approaching weak significance (significant at the 0.2 level) in the combined specification. This may suggest further investigation.

When considering the pandemic and post-pandemic years specification, both private insurance and self-pay show up with negative coefficients, albeit only significant at the 0.2 level. However, in the occupancy specification, the coefficients on both are positive, and significant at the same level for self-pay, and the coefficients are negative and insignificant in the combined model.

However, further examination shows more significant results, as pandemic year, as in previous specifications, shows a positive coefficient - though in this case only significant at the 0.05 level as opposed to the 0.001 level. This holds in the combined model as well. However, the post-pandemic year has a negative coefficient, significant at the same level. This disappears in the combined model, when accounting for occupancy. This may suggest that changes hospitals made after the 2009 flu pandemic affected future mortality through occupancy, such as by increasing bed counts. However, as overall hospital occupancy was not noticeably affected by the 2009 pandemic, it would be somewhat surprising if such changes showed up in the overall occupancy measure. Further investigation is necessary to determine if this is the case.

Quite unexpectedly, private insurance shows a significant positive coefficient in interactions with pandemic year and post-pandemic year. This pattern continues in the combined specification, which suggests that flu patients with private insurance are 1.95 times as likely to die in a pandemic year as Medicare patients, and 1.64 times more likely in a post-pandemic year. These results are significant at the 0.05 level in the combined specification. This may be partially due to heterogeneity in private insurance types. Less surprisingly, Medicaid has a positive coefficient for both pandemic and postpandemic years in both the pandemic and combined specifications, suggesting the pandemic and post-

pandemic years have been differentially worse for mortality outcomes for lower-income flu patients on Medicaid, though these coefficients are only approaching marginal significance (0.2 level).

Interestingly, self-pay also has a positive coefficient for both pandemic and post-pandemic years in both specifications. These are significant at the 0.01 level for pandemic years and 0.05 for post-pandemic years, suggesting that patients who are expected to self-pay - and therefore presumably do not have insurance - are 7.26 times more likely to die than Medicare patients in a pandemic year, and 4.76 times more likely in a post-pandemic year. This result suggests that patients without insurance could be at a large and significant disadvantage during pandemics, even controlling for baseline health risk via the age-adjusted Charlson, and for hospital fixed effects. Whether this is due largely to other health risk factors occurring at higher rates among patients without health insurance, or to discrimination against patients without health insurance, other factors, or some combination, is unclear, but this suggests a need for further investigation in order to better approach and correct these disparities.

Conclusions and Discussion

Several findings were as expected. For one, the regressions further validated the use of ageadjusted Charlson for flu mortality, as the relationship between the age-adjusted Charlson and the mortality risk was consistently positive and highly significant. Further, both graphs and regressions consistently confirm the significance of the 2009 H1N1 in flu hospitalizations and mortality. However, both post-pandemic years and hospital occupancy by quarter appeared to have less significance.

Overall, the results for Black and Hispanic patients were not what would have been expected given known disparities for flu mortality. Further, the interaction between race and hospital crowding or pandemic measures was not clear cut or as expected. This may suggest that racial disparities in mortality are not conditional on hospitalization, but rather arise from disparities prior to hospitalization. It is well established that such disparities exist, such as disparities in vaccine rates and access, (Hebert et al 2005, Schwartz et al 2006, CDC 2010B, Bardenheir et al 2011), 'separate and

unequal' primary care, persistent degrees of segregation of outpatient care and nursing homes as well as hospitals, (Smith, 2005), lower access to healthcare, whether due to geographical location or insurance, as well as potential language barriers, (KFF, 2008) and receipt of lower quality care from other health care practitioners, (Bridges, 2018) among many others. However, disparities conditional on hospitalization cannot yet be ruled out.

The results for Hispanic patients, and particularly Hispanic women, suggest further exploration. There is some suggestion that male Hispanic patients may be worse off in terms of flu mortality in this data, but female Hispanic patients may be better off, even controlling for reduced flu mortality risk for female patients versus male patients overall. This may play a role in driving lower overall flu mortality for Hispanics, if this California data is reasonably representative of the whole country. However, hospital occupancy seems to drive this in opposite directions, where Hispanic women become worse off while the Hispanic coefficient overall - and therefore Hispanic men become better off. There is also some suggestion that Black women specifically may be worse off in terms of flu mortality. These findings suggest that this question should be further examined with a larger sample across multiple states in order to assess significance and representativeness of these findings. Potential mechanisms for such an effect are currently unclear, but additional data may illuminate them.

Perhaps the most striking result is the higher mortality rate for patients who are expected to self-pay - patients, presumably, without insurance - during the pandemic year. This may suggest that patients without insurance are especially worse off in pandemic years. However, self-pay on its own has no significance, and there appears to be no impact from occupancy ratio as well.

Several next steps are suggested. Most readily apparent would be considering a broadening of the data pool to consider more states. This would be especially useful in determining whether the marginally significant or approaching marginally significant results are actually significant or the product of noise.

Another next step includes examining why occupancy appears to have relatively little impact. Several steps could potentially refine this measure and develop alternate measures that may more

accurately capture hospital strain relative to resources for flu patients. For instance, one might consider distributions of bed types, or consider the load of flu patients specifically, or patients with respiratory conditions that might require similar treatment to flu.

There may be further considerations in analyzing flu mortality - for instance, consider the severity of the flu case. It may be possible to proxy for this by considering whether patients come in with pneumonia, or are emergency admits. Additionally, one could examine mechanisms for differential outcomes by examining the procedures data to determine which patients were more likely to receive certain procedures, or a greater number of procedures.

Further, one may consider how patient choices relate and respond to hospital crowding and flu pandemics, and how other selection is incorporated into what hospitals patients are treated at. Patients may intentionally avoid hospitals known to be dealing with overcrowding, or be redirected if space is limited. Patients may also be more likely to go to a hospital during a pandemic, because of increased concerns about infectious disease, or less likely, to avoid contact with potentially infectious patients. One could examine patients' arrivals (emergency admittance, transfer, etc.) to look for patterns of choice.

Any comparison of these results, particularly regarding the 2009 H1N1 pandemic, with the current Covid-19 pandemic must consider several distinguishing features, such as differences in the features of the disease as well as differences in the impact upon hospitals. Any comparison must consider the differences in how these two pandemics impacted hospital crowding, particularly over time.

This area of research shows promise for future investigation, and is an important part of considering how we may address racial health disparities in the future.

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