COVID-19 and the Impact of Statewide Eviction Moratoriums on Eviction Rates

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Introduction

The sudden economic downturn induced by the COVID-19 pandemic was felt by many individuals and businesses across the country. The consequential layoffs and cuts in hours caused widespread job and housing insecurity. In order to assist those who could no longer afford to pay rent because of these economic effects, a temporary eviction moratorium was established as part of the Coronavirus Aid, Relief, and Economic Security (CARES) Act. This initial halt in evictions began on March 27, 2020 and lasted until July 24, 2020. There was then no federal eviction moratorium in place until September 4, 2020 when the CDC ordered a halt in evictions, which is still currently in place.

Not all properties or renters are covered by the federal moratorium, however. The primary requirement is that the rental unit itself has to be financed by a federally backed mortgage loan. Therefore, of the 43.8 million rental units in the United States, only 12.3 million units are covered by the CARES Act (Benfer et al., 2020). Additionally, renters must have "demonstrated effort to obtain government assistance for housing, are unable to pay full rent because of loss of income, are attempting to partially pay rent, and would become homeless or have to move into a shared living setting" if they were evicted (O'Connell, 2021). They also must meet one of the following criteria: "expect to earn no more than $99,000 (individuals) or $198,000 (filing joint tax return) in 2020, not have been required to report any income to the IRS in 2020, or have received an Economic Impact Payment (stimulus check)" (O'Connell, 2021). Some states issued their own eviction protection orders that allowed more people to be eligible based on factors such as needing to care for a child, a disabled person, or other relative. Many of these statewide moratoria ended before or after the July 24th cutoff of the CARES Act federal moratorium (Table 1). If a state did not currently have an eviction moratorium in place, tenants were protected under the federal moratorium.

This study's question of interest is how statewide eviction moratoria impacted the number of evictions per day for zip codes in 27 different cities from March 27, 2020 to September 4, 2020. This paper will also look at the majority race by census tract and changes in consumer spending and employment levels by city to determine their correlation with the number of evictions since those factors could influence the magnitude of the pandemic's financial repercussions on individuals. Overall, the number of people evicted during this health crisis is necessary to study because of its potential consequences. Moving during the pandemic presents health risks, especially if someone is already coming from a low-income and higher-incidence rate area or having to move into a shared living space - exacerbating existing health inequities. Additionally, because of the economic recession, if people are evicted from their homes and struggling to find a job or keep a steady income, they face a greater risk of homelessness which can lead to lifelong effects. Therefore, studying the rate of evictions and correlating factors during the COVID-19 pandemic could help predict these outcomes and inform about what solutions could best be implemented to help those affected.

Previous Literature

Because of the seriousness of the potential consequences of being evicted on a person's wellbeing, many researchers have focused on the eviction moratoria and their related issues. In one such study entitled "Housing Precarity & the COVID-19 Pandemic: Impacts of Utility Disconnection and Eviction Moratoria on Infections and Deaths Across US Counties," Jowers uses a panel regression model to analyze how evictions lead to an increase in COVID-19 infections and how policies could limit these impacts. He found that because evictions and utility shut-offs create harder environments for people to maintain social distancing guidelines and hygiene recommendations, policies that limit evictions - such as eviction moratoria - could reduce COVID-19 infections by 3.8% and deaths by 11% (Jowers et al., 2021). Additionally, he found that "had such policies been in place across all counties (i.e., adopted as federal policy) from early March 2020 through the end of November 2020, our estimated counterfactuals show that policies that limit evictions could have reduced COVID-19 infections by 14.2% and deaths by 40.7%" (Jowers et al., 2021). This possibly indicates that the break in the federal moratoria from late July through September caused severe health losses.

In another study entitled "Expiring Eviction Moratoriums and COVID-19 Incidence and Mortality," Leifheit also studies how eviction moratoria corresponded with COVID-19 infections and deaths; however, similar to this paper, he analyzes the expirations of state-level policies from March through September. He also uses a difference-in-difference approach but with state and week fixed effects rather than city and day fixed effects. He found that "COVID-19 incidence in states that lifted their moratoriums was 1.6 (95% CI 1.0,2.3) times the incidence of states that maintained their moratoriums at 10 weeks post-lifting and grew to a ratio of 2.1 (CI 1.1,3.9) at ≥16 weeks" (Leifheit et al., 2020). Overall, this supports the idea that eviction moratoria are effective in limiting the spread of COVID-19.

In a third paper, "COVID-19 rental eviction moratoria and household well-being," authors An, Gabriel, and Tzur-Ilan use panel data to investigate how changes in households' spending patterns due to state and county-level eviction moratoria impacted their well-being - defined by levels of food insecurity and mental stress. Because of the eviction moratoria, families were able to redirect their finances towards paying for groceries, therefore increasing food security. The authors also studied these trends across different racial and ethnic groups and found that African American households benefited the most from these eviction policies. As with the data collected for this paper, authors An, Gabriel, and Tzur-Ilan use zip code level data from March through August in combination with Opportunity Insight's credit card usage data. To assess mental health they used data from the Census COVID-19 Household Pulse Survey (An et al., 2021).

Overall, the goals of these papers are all to determine whether the eviction moratoria were successful in bettering some aspect of the population - either health, financial, or general wellbeing. Yet, this paper will focus more on eviction moratoria, consumer spending, and employment and their relationship with the number of evictions themselves rather than how the eviction moratoria influenced those financial effects. This paper expands upon the other studies by examining these trends at the zip code and day level - a more specific lens than some of the other studies, which can pick up on details that might be generalized at a state or week level. More importantly, this paper can show what factors among a zip code's population lend themselves to a greater rate of eviction, therefore contributing to the well-being effects researched by these other authors.

Economic Model

The four models included in this paper analyze the associations between a combination of independent variables, including demographic, economic, and other factors, and our dependent variable - the number of evictions filed per day in an individual zip code. They are all forms of difference-in-difference models which, because of the parallel trends assumption, allow any changes observed to be attributed to the treatment - the removal or absence of the state-level eviction moratorium.

The first model (1) includes the after moratorium removal variable as well as majority race variables. It also holds constant city and day fixed effects. These fixed effects correct for the possibility that any changes seen are due to differences between the cities or days themselves. The city fixed effects could include time-invariant characteristics such as population (assuming population does not vary drastically in the eight month period studied) where by having more people, a zip code would have more evictions. The time fixed effects account for influences such as other policies implemented at the national level that would have been outside forces impacting the number of evictions.

We also included race variables since the pandemic has affected minorities disproportionately, and these effects would most likely play a role in eviction rates as well. Because of this, the majority latinx and majority black variables are expected to have a positive coefficient indicating that a zip code in a city with a primarily latinx or black population was associated with a greater number of evictions in 2020. The after moratorium removal variable is the main variable that will be looked at to indicate the overall impact of not having a state-level eviction moratorium in place on eviction rates. Its expected coefficient sign is also positive. When states revoked their individual eviction policies, they defaulted to the federal eviction moratorium; however, it excluded a lot of people, many individuals were not aware of it, and it then expired during the summer, so landlords were able to evict more of their tenants. The goal of this model is to gain an initial and broad understanding of the relationship between these moratoriums and eviction rates before fine tuning the models to include other important variables.

The second model (2) is the same setup as the first model, except it also includes variables accounting for employment rates. There are three variables that indicate the association between employment levels of low, middle, and high income individuals and their numbers of evictions. This is a necessary factor to analyze since unemployment is a primary financial loss that could cause someone to stop paying rent and have to get evicted. The expected sign for all three variables is negative because as the employment rate increases, people should be more financially stable, and consequently the number of people evicted should decrease.

The third model (3) includes a variable looking at consumer spending in addition to the previously mentioned variables. Along with employment rate, consumer spending is an indicator of how well a city is doing financially. If consumer spending increases, that means more money is circulating in that city's economy and its residents will be better able to afford rent. We therefore expect the variable's sign to be negative showing that as consumer spending increases, there are less evictions.

The fourth and most comprehensive model adds greater analysis to the majority race variables by acting as a triple difference-in-difference with interaction terms between the race and after removal of the moratorium variables. This enables insights into how the moratoriums more specifically impacted the different races. These various groups might be more or less likely to be covered by the eviction policies both at the federal and state level. Therefore, the expected sign of a majority white, black or latinx zip code is negative indicating that relative to zip codes in cities with other racial group majorities, the removal of the moratorium caused a fewer number of evictions.

Data Collection

The data used in this study was collected from multiple sources. Princeton's Eviction Lab all-cities panel data includes information about specific zip codes and census tracts of 27 cities (Hepburn et al., 2020). The data is broken down by day with its reported number of filed evictions in 2020 and in previous years (average from 2012-2019). This dataset also displays information about the majority race of each census tract. The dates used from this dataset are all between March 27, 2020 and September 04, 2020, since that includes the starting date of the CARES Act federal moratorium and many state moratoriums and the date right before the next federal moratorium was announced.

The remaining data used was obtained from the Opportunity Insights database (Chetty et al., 2020). One of its panel data sets focuses on employment information which includes the daily change in employment rate compared to January of 2020 for all incomes and also broken down by low, middle, and high incomes. There is also information available about employment rates of different business sectors; however, this study chose not to analyze those factors. Another panel data set from Opportunity Insights includes information about the daily change in consumer spending broken down by type of franchise - food, food services, recreation/entertainment, general merchandise, healthcare, and transportation. The spending variable included in this study is the aggregate spending across all of these categories. For both datasets obtained from Opportunity Insights, the city and city id were included which were used to combine the three different datasets from both Opportunity Insights and the Princeton Eviction Lab. Additionally, dates of each state's eviction moratorium suspension were obtained from the paper "COVID-19 Eviction Moratoria & Housing Policy: Federal, State, Commonwealth, and Territory" by authors Benfer, Koehler, and Alexander and can be seen in table 1.

As mentioned in the explanation of the paper's models, the variables analyzed include majority race, employment rates, consumer spending rates, the number of filings in 2020, and whether a state's moratorium was suspended. These variables can be seen in the summary statistics table (Table 2) with their means, standard deviations, minimum values, and maximum values. The primary dependent variable of interest is the filings_2020 variable. This captures the total number of evictions filed on a specific day for that individual zip code or census tract. A mean of 0.396 and standard deviation of 2.783 indicate that many days had no evictions filed and when they did they were limited in number.

The main independent variable of interest is the after_mor variable. This is a dummy variable where, using the dates provided in table 1, a value of 1 indicates that the state's moratorium was no longer in place on the given day of the observation and a value of 0 indicates that it was. States that never issued their own moratorium and only followed the federal moratorium were automatically assigned a value of 1. States whose moratorium had not ended in the range of dates studied were automatically assigned a value of 0. A mean of 0.345 and standard deviation of 0.478 indicate that for most of the days in the dataset the states had an eviction moratorium in place. The Eviction Lab's data was used to evaluate the impact of race on evictions. There are four primary race variables - white_maj, latinx_maj, black_maj, and other_maj. Each of these is a dummy variable where a value of 1 demonstrates that the specified census tract has a majority population of the given race and a value of 0 if it does not. The white_maj variable has the highest mean of 0.498 - telling us that most of the census tracts have a majority white population. There are additional race-related variables, wht_after, latinx_after, black_after, and other_after, which are interaction terms between the race variables just mentioned and the after_mor variable. A value of 1 means that the zip code has a majority population of the indicated race and is in a state whose moratorium is not in place anymore and a value of 0 meaning at least one of those conditions was not met. Because most of the days in the study still have an active state moratorium, all of these variables have a mean value closer to zero.

The spend_all variable was provided by the Opportunity Insights data, and because of this there are fewer observations than the previously mentioned variables. Spend_all is the credit and debit card spending in all merchant categories for that day relative to January 2020. The mean of -0.140 and standard deviation of 0.125 indicate that for most of the days in the data set, spending was down compared to January. Its expected value is negative since as spending increases, people should be more financially stable and therefore the number of evictions should decrease. Emp_combined_low, emp_combined_middle, and emp_combined_high are additional economic variables that represent the employment rate for each income level on the given day compared to January 2020. All three variables have a negative mean indicating that for most days the employment rate was lower than in January. These are also expected to have a negative coefficient since as employment levels increase, evictions should decrease.

The remaining variables are used for the city and date fixed effects. The variable used to numerically keep track of the cities present in the study is cityid. Most of these are integer values that were already assigned to the cities present in the Opportunity Insights data. The remaining cities not present in the Opportunity Insights data were then assigned their own values. Dummy variables for the 27 cities used in the regressions were then made with 1 meaning the observation was from that city and 0 meaning it was not. The real date variable indicates the date in a format where each integer could be converted to a dummy variable.

Empirical Results

The results obtained are consistent with the main hypothesis of the study - the absence of a statewide eviction moratorium is associated with an increase in a zip code's number of evictions per day. Looking at table 7, the after_mor variable has the expected positive sign for each model and is statistically significant at the five percent level for three of the four models.

The positive coefficient indicates that observations in a state that has no current eviction policy correspond to an increase in the number of evictions in a day. The magnitude varies across the models, with model 1 having a coefficient of 0.348, model 2 having a coefficient of 0.132 (which was not statistically significant), model 3 having a coefficient of 0.318, and model 4 having a coefficient of 0.625. The statistically significant coefficients tell us that it is likely not due to chance that a zip code in a state with no eviction moratorium in place is correlated with an increase by less than one eviction per day. Although this magnitude is relatively small, if that result occurred for the multiple months present in the study, it would accumulate to a sizable number of additional evictions.

The first model had all statistically significant coefficients. Besides the after_mor variable, this model also included the white_maj, latinx_maj, and black_maj variables relative to the omitted group of the other racial category. The white_maj variable had a coefficient of -0.258. This has the expected negative sign because due to socioeconomic factors, majority white zip codes are more likely to be more financially stable compared to zip codes with a majority race other than black or latinx. The magnitude of the coefficient indicates that compared to these other zip codes, a zip code that is white is associated with 0.258 fewer evictions per day. The other race variables also have the expected sign. The coefficients for a majority latinx zip code and a majority black zip code indicate that compared to other areas, these areas are associated with 0.132 and 0.157 additional evictions per day respectively. As with the majority white zip codes, these signs are expected since socioeconomic factors cause zip codes in majority latinx and black cities to be less financially stable. These magnitudes, along with the remaining race magnitudes in the following models, are meaningful since if these numbers were replicated for multiple weeks, that would give an increase of possibly 30 additional evictions for a single latinx or black majority zip code.

Model 2 had fewer statistically significant variables, with only the white and latinx race variables and high income employment variable being statistically significant. All of the race variables were negative with white_maj having a coefficient of -0.503, latinx_maj having a coefficient of -0.268, and black_maj having a coefficient of -0.070. Although the black and latinx race variables had a previously positive sign, it is not unexpected for them to have a negative sign either since they are relative to the omitted group. It would be understandable for latinx and black majority zip codes to have fewer evictions per day than zip codes with other racial majorities. The additional variables included in this model are the employment variables. The emp_combined_inclow had a coefficient of 0.656, the emp_combined_incmiddle had a coefficient of -4.428, and the emp_combined_inchigh had a coefficient of 11.201. The middle income employment variables were the only ones with the expected sign. It was expected that as employment increased across any of the levels of income, the number of evictions would decrease. The statistically significant coefficient of the high income group is therefore very surprising especially given its magnitude since that would indicate that the increase of high income employment by a percentage point is associated with 11.201 additional evictions which is far greater than any of the other results. This could possibly be due to the trends we saw in employment in different business sectors. Many low income individuals lost their jobs while high income individuals were not nearly as affected. If employment in high income jobs increased, then there may have been a subsequent decline in low income employment and therefore an increase in evictions that the high income employment variable was accounting for. Additionally, the switch in the race variables' signs could also be due to effects from the employment variables. Since the associations in both the race and employment variables are possibly both due largely to the same financial trends of zip codes, then the associations we initially saw in model 1 with the race variables might have been transferred to the employment variables in the remaining models 2-4.

In model 3 we see many of the same trends with the previously analyzed variables - all of the race and employment variables keep the same sign as model 2 and have very similar magnitudes. Yet, in model 3 all of the employment variables are statistically significant. The added variable in this model is spend_all which has a coefficient of -1.588. Given that it has the expected negative sign and is statistically significant, this tells us that there is an association between an area's spending and eviction rate - as spending relative to January 2020 increases by a percentage point, the number of evictions for that zip code and day decreases by 1.588.

Model 4 has many of the same signs and magnitudes as models 2 and 3 for the employment and spending variables; however, there are some differences with the latinx_maj and black_maj variables. In this model, the latinx majority variable is not statistically significant and has an extremely small positive magnitude. Although the magnitude tells us that this coefficient is not extremely meaningful to the study, it does fall more in line with what was expected given the socioeconomic factors mentioned above. Additionally, the black majority variable was not statistically significant, but like the latinx variable, it changed to the expected positive sign. The added variables in this model are the interaction terms between the after moratoriums ended variable and the majority race variables. All of these terms had the expected sign given that they were relative to the other_after variable. The coefficient for wht_after indicates that zip codes in states with no eviction moratorium and a majority white population are associated with a decrease by 0.526 evictions per day relative to cities with a majority race other than white, black, or latinx. This same interpretation can be applied to the latinx_after and black_after variables with coefficients of -0.393 and -0.084 respectively. Although the black_after coefficient was not significant at the 5% level, its t-value was still relatively high indicating that it could still be meaningful to the study. These coefficients tell us that the other racial category was the most negatively impacted by the absence of eviction policies, and the white racial category was the least negatively impacted.

The changes in variable significance across the models is most likely due to the differences in number of observations and variables. Between model 1 and 2, almost half of the observations were dropped since the employment variables were only present in the Opportunity Insights data. Fewer observations for specific subsets of variables could cause less confidence in some of the trends seen. This could be especially relevant to the black_maj variable and its trends - most of the cities were either white, latinx, or other majority, so the black_maj had limited data to support its associations therefore possibly causing it to be statistically insignificant. In future studies, it would be ideal to not have any missing data. If employment and spending data could have been collected for each city and more cities with a majority black population were included, then some of the correlations seen may have been better supported. Yet, even with the decline in number of total observations, many variables were still statistically significant in the final models. This is most likely due to the individual cities having a large range and number of dates with observations.

Conclusion

The positively signed and statistically significant coefficient on the variable representing the suspension of a state eviction moratorium indicates the impact of these policies on the number of evictions that took place during the COVID-19 pandemic - the eviction moratoriums were successful in lessening the number of evictions that took place. Due to the parallel trends assumption given by the difference-in-difference model, these policies must be responsible for the changes in the number of evictions that are seen between the dates before and after states revoke their eviction holds. Additionally, those who benefited the most from the presence of these policies include zip codes with a majority white population. Racial groups other than white, black and latinx were put at the greatest disadvantage by the removal of the state-level moratoriums. In terms of financial factors, zip codes in cities with greater consumer spending saw fewer evictions in general.

The ambiguous trend displayed by the employment variables with the unexpected coefficients in both magnitude and sign provide an opportunity for future research. Since omitted variable bias is most likely present, a study looking into what those missing variables are would allow us to correctly break down the association between employment and the number of evictions. Another possible study would be to look further into the relationship between the other racial category and eviction moratoriums and determine the reasons that group is hurt the most by the policies' removal. Within that category there are many subgroups, so it would be beneficial to look at these races individually since there are socioeconomic factors that affect them differently. In all of these additional studies, I would like to have a more complete dataset. Because I combined two different sources of data, it did not align perfectly and a lot of data was either missing for some cities or some cities had to be removed entirely. If I could find data for each observation, it would possibly allow more of the variables to be statistically significant, and the trends seen would be better supported.

Overall, the research on this topic conducted in this paper and in the future is important in helping us evaluate the impact and success of eviction policies implemented because of

COVID-19. It also provides us with the understanding of the specific types of areas of the country that had the most evictions, either due to demographic or financial reasons. If we know which and why certain cities are prone to more evictions, it can aid policy makers in implementing support systems targeted towards these factors. Not only can these policies directly reduce evictions, but they would also relieve some of their harsh consequences, such as moving into crowded housing and homelessness, that especially cannot be afforded during the COVID-19 pandemic.

Appendix

Models:

1) $filings\_2020_{ct} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 after\_mor_{ct} + \boldsymbol{\beta}_2 wht\_maj_c + \boldsymbol{\beta}_3 latinx\_maj_c + \boldsymbol{\beta}_4 black\_maj_c + \boldsymbol{\delta} city_c + \boldsymbol{\delta} date_t + e_{ct}$
2) $filings\_2020_{ct} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 after\_mor_{ct} + \boldsymbol{\beta}_2 wht\_maj_c + \boldsymbol{\beta}_3 latinx\_maj_c + \boldsymbol{\beta}_4 black\_maj_c + \boldsymbol{\beta}_5 emp\_combined\_inclow_{ct} + \boldsymbol{\beta}_6 emp\_combined\_incmiddle_{ct} + \boldsymbol{\beta}_7 emp\_combined\_inchigh_{ct} + \boldsymbol{\delta} city_c + \boldsymbol{\delta} date_t + e_{ct}$
3) $filings\_2020_{ct} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 after\_mor_{ct} + \boldsymbol{\beta}_2 wht\_maj_c + \boldsymbol{\beta}_3 latinx\_maj_c + \boldsymbol{\beta}_4 black\_maj_c + \boldsymbol{\beta}_5 emp\_combined\_inclow_{ct} + \boldsymbol{\beta}_6 emp\_combined\_incmiddle_{ct} + \boldsymbol{\beta}_7 emp\_combined\_inchigh_{ct} + \boldsymbol{\beta}_8 spend\_all_{ct} + \boldsymbol{\delta} city_c + \boldsymbol{\delta} date_t + e_{ct}$
4) $filings\_2020_{ct} = \boldsymbol{\beta}_0 + \boldsymbol{\beta}_1 after\_mor_{ct} + \boldsymbol{\beta}_2 wht\_maj_c + \boldsymbol{\beta}_3 latinx\_maj_c + \boldsymbol{\beta}_4 black\_maj_c + \boldsymbol{\beta}_5 wht\_after_c + \boldsymbol{\beta}_6 latinx\_after_c + \boldsymbol{\beta}_7 black\_after_c + \boldsymbol{\beta}_8 emp\_combined\_inclow_{ct} + \boldsymbol{\beta}_9 emp\_combined\_incmiddle_{ct} + \boldsymbol{\beta}_{10} emp\_combined\_inchigh_{ct} + \boldsymbol{\beta}_{11} spend\_all_{ct} + \boldsymbol{\delta} city_c + \boldsymbol{\delta} date_t + e_{ct}$

Table 1. Expiration dates of statewide eviction moratoria

State	Moratorium expiration	State	Moratorium expiration
Idaho	4/20/2020	Kentucky	8/25/2020
North Dakota	4/22/2020	Pennsylvania	8/31/2020
South Carolina	5/14/2020	Arizona	Not lifted
Utah	5/15/2020	California	Not lifted
Virginia	5/17/2020	Connecticut	Not lifted
Texas	5/18/2020	Florida	Not lifted
West Virginia	5/18/2020	Hawaii	Not lifted
Iowa	5/27/2020	Illinois	Not lifted
Wisconsin	5/28/2020	Massachusetts	Not lifted
Alabama	5/31/2020	Minnesota	Not lifted
Kansas	5/31/2020	Montana	Not lifted
Mississippi	5/31/2020	Nevada	Not lifted
Nebraska	5/31/2020	New Jersey	Not lifted
Tennessee	5/31/2020	New Mexico	Not lifted
Colorado	6/13/2020	New York	Not lifted
Louisiana	6/15/2020	Oregon	Not lifted
North Carolina	6/20/2020	Vermont	Not lifted
Alaska	6/30/2020	Washington	Not lifted
Delaware	7/1/2020	Arkansas	N/A
New Hampshire	7/1/2020	Georgia	N/A
Rhode Island	7/1/2020	Missouri	N/A
Michigan	7/15/2020	Ohio	N/A
Maryland	7/25/2020	Oklahoma	N/A
Maine	8/3/2020	South Dakota	N/A
Indiana	8/14/2020	Wyoming	N/A

Table 2. Summary statistics

Variable	Observations	Mean	Std Dev	Min	Max
filings_2020	148,925	0.396	2.783	0	420
After_Mor	148,925	0.354	0.478	0	1
white_maj	148,925	0.498	0.499	0	1
latinx_maj	148,925	0.132	0.339	0	1
black_maj	148,925	0.142	0.349	0	1
other_maj	148,925	0.223	0.416	0	1
wht_after	148,925	0.147	0.354	0	1
latinx_after	148,925	0.058	0.235	0	1
black_after	148,925	0.068	0.252	0	1
other_after	148,925	0.078	0.268	0	1
cityid	148,925	18.108	14.489	2	46
spend_all	137,195	-0.140	0.125	-0.509	0.189
emp_combined_inclow	92,207	-0.189	0.066	-0.399	-0.072
emp_combined_incmiddle	102,051	-0.065	0.041	-0.212	.0148
emp_combined_inchigh	119,738	-0.043	0.035	-0.165	.008
realDate	148,925	608.1739	152.1005	329	830
City DVs	148,925	--	--	0	1

Table 3. Regression results from model 1

	Coefficient	Standard Error	T-Stat	P-value
After_Mor	0.348**	0.030	11.737	0.000
white_maj	-0.258**	0.019	-13.695	0.000
latinx_maj	0.132**	0.025	5.206	0.000
black_maj	0.157**	0.026	6.044	0.000

**Statistically significant at the 95% confidence level

Table 4. Regression results from model 2

	Coefficient	Standard Error	T-Stat	P-value
After_Mor	0.132	0.138	0.953	0.341
white_maj	-0.503**	0.038	-13.149	0.000
latinx_maj	-0.268**	0.042	-6.445	0.000
black_maj	-0.070	0.051	-1.381	0.167
emp_combined_inclow	0.656	1.622	0.404	0.686
emp_combined_incmiddle	-4.428	3.113	-1.422	0.155
emp_combined_inchigh	11.201**	3.428	3.270	0.001

**Statistically significant at the 95% confidence level

Table 5. Regression results from model 3

	Coefficient	Standard Error	T-stat	P-value
After_Mor	0.318**	0.064	4.927	0.000
white_maj	-0.419**	0.029	-14.373	0.000
latinx_maj	-0.214**	0.035	-6.205	0.000
black_maj	-0.026	0.040	-0.652	0.515
emp_combined_inclow	2.564**	0.971	2.640	0.008
emp_combined_incmiddle	-3.160**	1.462	-2.161	0.031
emp_combined_inchigh	11.153**	3.430	3.250	0.001
spend_all	-1.588**	0.470	-3.378	0.001

**Statistically significant at the 95% confidence level

Table 6. Regression results from model 4

	Coefficient	Standard Error	T-Stat	P-value
After_Mor	0.625**	0.076	8.201	0.000
white_maj	-0.157**	0.041	-3.812	0.000
latinx_maj	0.000	0.054	0.001	0.999
black_maj	0.012	0.060	0.194	0.847
wht_after	-0.526**	0.058	-9.109	0.000
latinx_after	-0.393**	0.070	-5.610	0.000
black_after	-0.084	0.079	-1.067	0.286
emp_combined_inclow	2.532**	0.971	2.608	0.009
emp_combined_incmiddle	-3.045**	1.463	-2.081	0.037
emp_combined_inchigh	11.203**	3.437	3.260	0.001
spend_all	-1.576**	0.470	-3.354	0.001

**Statistically significant at the 95% confidence level

Table 7. Combined coefficient results from models 1-4

	(1)	(2)	(3)	(4)
After_Mor	0.348**	0.132	0.318**	0.625**
white_maj	-0.258**	-0.503**	-0.419**	-0.157**
latinx_maj	0.132**	-0.268**	-0.214**	0.000
black_maj	0.157**	-0.070	-0.026	0.012
emp_combined_inclow		0.656	2.564**	2.532**
emp_combined_incmiddle		-4.428	-3.160**	-3.045**
emp_combined_inchigh		11.201**	11.153**	11.203**
spend_all			-1.588**	-1.576**
white_after				-0.526**
latinx_after				-0.393**
black_after				-0.084
Number of observations	186,093	71,254	71,254	71,254
Adj-R^2	0.0298	0.0107	0.0116	0.0130

**Statistically significant at the 95% confidence level

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