SAN DIEGO TAXPAYERS EDUCATIONAL FOUNDATION

Preliminary Indications of the Effects of Homelessness Expenditures on Point-In-Time Count

Research Question

Which type of expenditure in the area of homelessness (crisis management, diversion, or prevention) is most effective (and to what extent) in reducing the total number of people experiencing homelessness as indicated by the annual "Point in Time" count? To answer this, we explore correlations between the expenditures of the 18 cities in San Diego County and the number of people experiencing homelessness, controlling for likely variables which minimize bias (by city and year).

Data

The cities' expenditure data were manually cleaned and organized from homelessness expenditures requested from each city by the San Diego Taxpayers Educational Foundation's data science team. The Point-In-Time Count ("PIT") comes from the Regional Task Force on Homelessness ("RTFH"), which produces data on the number of people experiencing homelessness January of each year in each city in San Diego County. Researchers classified whether an expenditure is related to crisis management, prevention, or diversion, based on its specified program with confirmations by the eighteen cities' subject matter experts on homelessness expenditures. Classifications are defined by the US Interagency Council on Homelessness, as follows:

1. **Prevention:** Homelessness prevention strategies represent a wide array of efforts to prevent housing crises from occurring and to prevent people who face such crises from experiencing homelessness. Prevention strategies are described in "Home, Together", a strategic plan by the USICH to prevent and end homelessness, as falling into the

following categories: 1. Activities that reduce the prevalence of risk of housing crises within communities; 2. Activities that reduce the risk of homelessness while households are engaged with or are transitioning from systems; and 3. Activities that target assistance to prevent housing crises that do occur from escalating further and resulting in homelessness.(United States Interagency Council on Homelessness)

2. **Diversion:** Diversion, also known as Rapid Exit strategies are appropriate after a household has entered emergency shelter or has stayed in an unsheltered setting, and rapid exit strategies serve to help them move as quickly as possible back into housing with the support of services and a minimal level of financial assistance. (United States Interagency Council on Homelessness). Rapid exits are designed to help someone exit the system as rapidly as possible. Individuals who receive housing through a Coordinated Entry System referral are not considered as having rapidly exited. Additionally, rapid rehousing is not a rapid exit definitionally, though they sound similar. Diversion strategies and practices assist people to resolve their immediate housing crisis by accessing alternatives to entering emergency shelter or the experience of unsheltered living. This typically occurs at the point people request emergency services, such as entry into emergency shelter, or could take place in a day center or through outreach before a person spends a night unsheltered. Diversion is not a process of turning people away or declining to provide needed services. Rather, diversion offers a valuable service that helps people avoid the experience of being in shelter or unsheltered.(United States Interagency Council on Homelessness)
3. **Crisis Management:** Crisis management strategies or programs are those that work with individuals who were not prevented from homelessness and also were unable to rapidly exit from their homelessness experience

In order to ensure our model is maximally accurate and minimally biased, researchers aggregated the total amount spent in each of the three areas per jurisdiction and year and added several control variables. The median income data comes from the ACS 1-year surveys for San Diego county from each year 2017-2022. The average home value data comes from Zillow's ZHVI (Zillow Home Value Index), published on their website. Finally, the total expenditures data comes from a dataset from the CA Open Data Portal. The final dataframe contains columns

“City”, “Year”, “AVG_Home_Value”, “Total_Exp”, “Median_Inc”, “Population”, “Total_PEH”, “Crisis Management Amount”, “Diversion Amount”, “Prevention Amount”, “Total_Amount”, “PEH_Per_10000”, “Total_Exp_Per_10000”.

Limitations

The main challenge faced in this study which may affect the accuracy of results is the nature of the response variable. De-identified, individual-specific data on what dates people entered and exited homelessness are not publicly available. In fact, the data that is available on the number of homeless people is not even month-to-month. Instead, the PIT count only measures the total number of people who experienced homelessness throughout a full, calendar year. As required by HUD, each Continuum of Care (in this case the RTFH) measures and stores the de-identified data described above. If they would allow us to access it, researchers could perform a more robust analysis, which could give the community better insight into where the best solutions for combatting homelessness may lie. Our definition for “effective” is when an individual exits to permanent housing of any type and does not return to homelessness for at least one year, and with the data that we know RTFH could provide – as they have before – the expenditures could be tied to what is and is not effective to result in a study much more robust than what is presented here.

Another potentially confounding variable, which researches were unable to obtain, is law enforcement interactions. Since different cities have varying policies on how law enforcement interacts with homeless people, one could suggest that a city with a lower PIT count per 10,000 may have achieved such a number because their law enforcement incarcerates or transports its homeless population.

Understanding this, it must be noted that the true extent to which homelessness expenditures affect the number of people experiencing homelessness will not be fully encapsulated by the proceeding analysis.

Hypothesis

The RTFH published a yearly report during November of 2022 which stated for every 10 people who exited homelessness, 13 people entered homelessness. When they released the same report one year later, the ratio had decreased from 10:13 to 10:16. Based on this information, researchers hypothesized the following: There is little observed correlation between total homelessness expenditures and the number of people experiencing homelessness. Factors outside of local government control like unemployment rate, inflation, etc. will appear to have a greater effect on the variation of number of homeless people than does government spending. As far as expenditure type, the most effective area of expenditure is predicted to be prevention, as preventative measures are warranted when the rate at which people are entering homelessness is increasing.

Methodology & Analysis

To evaluate the observed effect of the type of homelessness expenditure on the number of people experiencing homelessness, a multivariate, ordinary least squares regression model is most appropriate. In order to eliminate bias as much as possible, we elected to add population data by city and year to our dataset and transform the total number of homeless people to total number of homeless people per 10,000. Of course larger cities like San Diego will have more homeless people than less populated cities like Santee. Secondly, we want to control for the level of affluence in our analysis, because it's well understood that there will be more people experiencing homelessness in cities where the median income is lower. Similarly, housing prices are important because naturally cities with higher housing prices will affect a person's ability to find permanent housing.

First, in order to understand broadly the effect of homelessness expenditures on the number of people experiencing homelessness. The following are the results of an ordinary least squares regression analysis, holding constant the city, median income, average home value, and total city expenditures per 10,000:

```
Call:
lm(formula = PEH_Per_10000 ~ Total_Amount + AVG_Home_Value +
    Total_Exp_Per_10000 + Median_Inc + City, data = final_table)

Residuals:
    Min      1Q  Median      3Q     Max
-16.864  -3.668   0.326   2.612  23.245

Coefficients:
                             Estimate Std. Error t value Pr(>|t|)
(Intercept)                 9.323e+01  2.638e+01   3.534  0.00110 **
Total_Amount                8.800e-07  1.842e-06   0.478  0.63550
AVG_Home_Value             -1.004e-04  5.801e-05  -1.731  0.09153 .
Total_Exp_Per_10000         8.538e-09  6.893e-07   0.012  0.99018
Median_Inc                  3.426e-05  5.204e-04   0.066  0.94785
CityCity of Chula Vista    -2.733e+01  8.946e+00  -3.055  0.00410 **
CityCity of Coronado        9.570e+01  5.892e+01   1.624  0.11258
CityCity of El Cajon        3.036e+01  1.652e+01   1.838  0.07395 .
CityCity of Encinitas       3.638e+01  1.927e+01   1.888  0.06675 .
CityCity of Escondido      -1.181e+01  1.368e+01  -0.863  0.39337
CityCity of La Mesa        -2.774e+01  1.212e+01  -2.289  0.02773 *
CityCity of Lemon Grove    -4.024e+01  1.215e+01  -3.311  0.00205 **
CityCity of National City  -2.966e+01  1.846e+01  -1.607  0.11633
CityCity of Oceanside      -5.500e+01  6.724e+01  -0.818  0.41850
CityCity of Poway          -1.941e+01  9.045e+00  -2.146  0.03829 *
CityCity of San Diego       1.099e+01  1.500e+01   0.732  0.46838
CityCity of San Marcos     -2.901e+01  9.434e+00  -3.075  0.00389 **
CityCity of Santee         -3.907e+01  1.155e+01  -3.383  0.00168 **
CityCity of Vista          -2.074e+01  1.051e+01  -1.974  0.05569 .
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.805 on 38 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.9011,    Adjusted R-squared:  0.8542
F-statistic: 19.23 on 18 and 38 DF,  p-value: 8.215e-14
```

The coefficient associated with total homelessness expenditures is positive, but its p value is very high. This means that, based on city expenditures from 2017-2022, there is a 63.55% probability that there is no relationship between expenditures in homelessness services and PEH per 10,000.

To dig deeper, researchers performed a regression analysis using the specific type of expenditure. Results are shown below.

```
Call:
lm(formula = PEH_Per_10000 ~ CM_Amount + D_Amount + P_Amount,
    data = final_table)

Residuals:
    Min      1Q  Median      3Q     Max 
-25.058 -16.717  -9.020   6.679 102.426 

Coefficients:
              Estimate Std. Error t value Pr(>|t|)    
(Intercept)  2.137e+01  3.688e+00   5.794 2.98e-07 ***
CM_Amount    8.669e-07  9.508e-07   0.912    0.366    
D_Amount     1.693e-05  3.158e-05   0.536    0.594    
P_Amount    -1.859e-05  1.421e-05  -1.308    0.196    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 26.34 on 58 degrees of freedom
Multiple R-squared:  0.02965,	Adjusted R-squared:  -0.02054 
F-statistic: 0.5908 on 3 and 58 DF,  p-value: 0.6235
```

Based on this preliminary regression analysis, it appears that Prevention is the only type of expenditure which actually reduces the number of people experiencing homelessness per 10,000. The p values are fairly high for each coefficient, indicating that without other controls, statistical significance cannot be established. Further analysis is warranted.

Next, we control for several other variables, including the city binary variable, total yearly expenditures by city, average home value, and median income.

```
Call:
lm(formula = PEH_Per_10000 ~ CM_Amount + D_Amount + P_Amount + 
    Total_Exp_Per_10000 + Median_Inc + AVG_Home_Value + City, 
    data = final_table)

Residuals:
    Min      1Q  Median      3Q     Max 
-14.936  -3.190   0.000   2.401  22.906 

Coefficients:
                            Estimate Std. Error t value Pr(>|t|)   
(Intercept)                9.079e+01  2.621e+01   3.465  0.00139 **
CM_Amount                  1.763e-06  2.261e-06   0.780  0.44064   
D_Amount                   1.016e-05  1.301e-05   0.781  0.43995   
P_Amount                  -8.596e-06  5.865e-06  -1.466  0.15142   
Total_Exp_Per_10000        5.334e-08  6.842e-07   0.078  0.93829   
Median_Inc                 8.427e-05  5.196e-04   0.162  0.87207   
AVG_Home_Value            -1.063e-04  5.757e-05  -1.846  0.07314 . 
CityCity of Chula Vista   -2.523e+01  8.967e+00  -2.814  0.00788 **
CityCity of Coronado       1.018e+02  5.853e+01   1.740  0.09040 . 
CityCity of El Cajon       3.075e+01  1.674e+01   1.837  0.07452 . 
CityCity of Encinitas      3.865e+01  1.911e+01   2.022  0.05063 . 
CityCity of Escondido     -6.655e+00  1.385e+01  -0.481  0.63370   
CityCity of La Mesa       -2.537e+01  1.217e+01  -2.085  0.04418 * 
CityCity of Lemon Grove   -3.862e+01  1.205e+01  -3.206  0.00282 **
CityCity of National City -2.670e+01  1.846e+01  -1.446  0.15669   
CityCity of Oceanside     -7.037e+01  7.971e+01  -0.883  0.38317   
CityCity of Poway         -1.923e+01  8.972e+00  -2.143  0.03896 * 
CityCity of San Diego      1.194e+01  1.514e+01   0.789  0.43550   
CityCity of San Marcos    -2.662e+01  9.433e+00  -2.822  0.00772 **
CityCity of Santee        -3.769e+01  1.147e+01  -3.286  0.00227 **
CityCity of Vista         -1.702e+01  1.065e+01  -1.598  0.11868   
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 8.699 on 36 degrees of freedom
  (5 observations deleted due to missingness)
Multiple R-squared:  0.9085,	Adjusted R-squared:  0.8577 
F-statistic: 17.88 on 20 and 36 DF,  p-value: 4.171e-13
```

When holding all else constant, this analysis indicates a positive correlation between Crisis Management and Diversion expenditures. Namely, those coefficients are 0.000001763 and 0.00001016, respectively. This means that for every increase in $1,000,000 in crisis management, 1.763 additional people per 10,000 are predicted to experience homelessness.

Similarly, for every additional $1,000,000 spent in diversion programs, 10.16 additional people per 10,000 are predicted to experience homelessness. The only area that shows a negative relationship between amount of money spent and fewer people experiencing homelessness per 10,000 is Prevention. More importantly, the p values for crisis management and diversion are very high, which means there is not sufficient evidence that there is any relationship between expenditures in these areas and number of homeless people. Conversely, the model predicts an 84.9% probability that, all else held constant, the true relationship between PEH per 10,000 and Prevention expenditures is negative. Specifically, the model predicts that for every additional $1,000,000 spent in prevention, 8.596 fewer people will experience homelessness.

Preliminary Indications

As has been analyzed and statistically tested, there is little to no observed relationship between homelessness expenditures as a whole and the number of people experiencing homelessness, as captured in the PIT, in San Diego County. That is, there is no sufficient statistical evidence to prove such a relationship. While we cannot draw a causal relationship, we can certainly conclude that the homelessness problem in the county may be beyond the reach of current practice, and is not being fully addressed by current spending.

It is important to note that although the regression models show that crisis management and diversion spending have positive coefficients, that does not necessarily mean that the expenditures themselves are causing more people to become homeless. What this does indicate, however, is that despite our expenditures throughout the years in homelessness services, San Diego county's homeless population continues to rise and the rate at which it rises is also increasing.

Of the three types of expenditures, prevention-related spending may be the most effective, or more accurately, the only type that is actually shown to correlate with a reduction in homelessness. This makes intuitive sense, considering the fact that each year, more people enter homelessness than leave homelessness, and the number of those who enter is increasing each year with respect to the number of those who exit.

It is possible that crisis management and diversion programs are necessary in combating homelessness, but we are not able to test for that econometrically due to the limitations as described. The San Diego Housing Commission successfully removed more than 10,000 individuals from the same time period during which this study was conducted, and without some of these programs, it is certainly possible the homeless epidemic would be worse. That said, an effective long-term solution could be to allocate a larger percentage of dollars in prevention programs.

There is an idiom that an ounce of prevention is worth a pound of cure, which might be worthy of serious consideration given the preliminary indications in this analysis.