Measuring the Hidden Effect of the Shadow Economy on Housing First Policy

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1 Abstract

In this research paper, we analyze how the underlying shadow economy in U.S. states affect the efficacy of the Housing First policy in reducing homelessness. As there are no officially reported measures of the underground economy, we estimate such levels through a Multiple-Indicators Multiple-Causes General Additive Model, providing us an estimated measurement of the latent economy levels. Then, we model a time and state-fixed effects regression to estimate the effect of the shadow economy on the Housing First policy. We find significance only at the 10% significance level, in only one of the six different regression specifications. For further research, obtaining a larger time period dataset as well as reformulating the definition of "homelessness numbers" and degree of implementation of the Housing First policy (explanatory variable) will be paramount.

2 Introduction

Homelessness has always been a critical issue in the United States due to its negative impacts on a both individual and government level. Without proper housing and income, homeless are much more vulnerable to mental and physical illnesses, resulting in higher mortality rates. Furthermore, children who are born into or enter homelessness participate in illegal underground activities such as drug trafficking and prostitution to sustain their lives, providing little opportunity in participating in the official labor force with stable jobs. With little leeway and stepping stones to escape homelessness, over 500,000 people and 100,000 children were homeless in 2016 on any given night (Henry et al. 2016).

Acknowledging the critical issue of homelessness and the necessity of effective governmental policy measures, in 2009 the federal government initiated the Rapid Re-Housing Program – also known as the Housing First program. Contrary to previous housing programs which required numerous requirements such as substance abuse education, a paying job, and meeting transitional housing payment schedules, the Housing First program bypassed all such steps to provide permanent housing to the homeless. The U.S. Department of Housing and Urban Development (HUD) provided initial funding to 23 Continuum of Care (CoC) programs – state and local homelessness reduction programs – to evaluate the efficacy of such a program. The results were positive: 12 months after exiting the program, only 10% of households re-entered homelessness in an evaluation report conducted by the HUD in 2016 (Burt, Culhane, and Khadduri 2016), and Utah experienced over 91% in reduction of chronic homelessness by 2015. (McEvers 2015).

However, little research has been done to test the efficacy of the Housing First program in areas with booming shadow economies. In these areas, homeless tend to rely more on the shadow economy for their source of income, leading to more chronic homelessness and de-motivation to escape it. In case of the Housing First program, the homeless may enjoy permanent housing at first; however, without proper education and requirements that were previously enforced in other housing programs, homeless may be less motivated to earn sustainable income from stable jobs while they are on permanent housing. They may still rely on their unofficial sources of income due to their participation in a large shadow economy, mitigating the effects of Housing First policy. In this research paper, I test such hypothesis, investigating the effects of a high level of street economy activity on reducing the efficacy of the Housing First program and its significance across different states and years in the United States.

3 Literature Review

Housing First program has grown in popularity as an evidence-based policy to assist the homeless, with much research and studies on the efficacy of the program. In Canada for example, researchers conducted a randomized controlled trial among the mentally ill homeless to measure the efficacy of Housing First combined with Assertive Community Treatment (ACT) or Intensive Case Management (ICM) on income and odds of obtaining competitive employment (Poremski et al. 2016). To predict the outcome variables retrospectively at 30-day intervals, researchers utilized Generalized Estimating Equations (GEEs) and logit link functions for their regression model. The study found that Housing First did help increase the odds of finding competitive employment, but not on income, demonstrating positive effects of Housing First program in Canada. Similarly in the United States, researchers analyzed Housing First's role in reducing homelessness numbers directly. In 2007, the HUD along with Health and Human Services (HHS) and Veteran Affairs (VA) conducted a joint study of reducing chronic homelessness in seven U.S. cities by utilizing the Housing First model (Mares and Rosenheck 2007). The study utilized a mixed regression model to take into account both time and and individual-level effects to measure whether the Housing First program, for a given homeless participant, improved the chance that the participant would remain out of homelessness with permanent housing provided at baseline. The Housing First program - combined with other intensive case management and access to health services - achieved 85 percent housing retention rates after twelve months. This aggregate study across seven different cities demonstrated the positive retentive impact of Housing First in the United States.

However another important aspect of homelessness is the prevalence of substance abuse and mental illness which impedes their ability to escape out of homelessness. Interviewing 471 random homeless adults in Alameda county, researchers aimed to measure impacts of substance abuse on employment and income for homeless by utilizing a logit probabilistic model (Zuvekas and Hill

2000). Drug and alcohol abuse, as expected, were positively correlated with higher probability to work lower number of work hours, and were negatively correlated with lower probability to work higher number of work hours. Furthermore, substance abuse limited homeless' participation in benefit and disability programs, closing even more possibilities of escaping homelessness. Therefore, the importance of substance abuse is evident when people try to escape homelessness. Even with the Housing First program, such negative activities related to homelessness may result in difficulty in helping the homelessness, especially in areas with booming street economies.

In similar direction of research, a study in Vancouver demonstrated no significant difference between levels of housing stability for homeless with mental disorders regardless of whether they possess substance dependence, in the Housing First program (Palepu et al. 2013), though not conducted on a geographic area level. The study utilized a negative binomial regression model to find the independent association between the residential stability substance dependence, and concluded no additional loss in efficacy of the Housing First program for substance-dependent homeless. While the paper specifically focused on individuals with substance abuse, it is important to further examine the aggregate, macroeconomic effects in areas with high drug abuse and booming underground economy, and how that may possibly spillover to homeless in general, affecting the impacts of the Housing First program in such areas regionally.

However, little research has been conducted on measuring the underground economy – which largely drive substance abuse among the homeless. As no official measure of the shadow economy exist, researchers have utilized indirect proxies such as cash demand and tax pressure to reflect an increase in the informal economy (Tanzi 1980). Economists also tested the Lackó method, using electricity consumption and its direct relation to GDP, measuring the difference between observed GDP and estimated via electricity (Lackó 2000). In recent years, many studies implemented a more model-based approach that not only uses a single proxy indicator, but uses the Multiple Indicators, Multiple Causes (MIMIC) method which generate an estimator for the unobservable latent variable using covariance between observed variables (Dell'Anno, Gomez-Antonio, and Pardo 2007). For example, a study generalized the MIMIC method to measure the level of shadow economy on the state-level in United States. Specifically in our research paper, we model and replicate the MIMIC model structured by Wiseman in his paper for the purpose of our research, to see its indicative effects on the homeless and Housing First policy (Wiseman 2013).

Preexisting literature have focused extensive analysis on the effects of Housing First program on an aggregate level in many areas - United States and abroad - on outcomes in employment, income, and reduction in homeless numbers. On a separate but related area of interest, researchers have also studied the impact of substance abuse on the homeless on individual levels, and in one literature connecting substance abuse to the efficacy of the Housing First program. However, our paper aims to connect the two areas of research together through the prevailing shadow economy – that the shadow economy induces negative behaviors such as drug abuse, and how that may change the impact of the Housing First program. Insufficient amount of research exists on measuring and utilizing the underground economy and its impacts on the homeless, which we hope to add to the literature by specifically focusing on the Housing First program and its reduction in homeless numbers.

4 Description of Data and Model

4.1 Homeless Numbers and the Housing First Program

To test the hypothesis that the Housing First program will be less effective in areas with thriving shadow economy, I first obtained data from HUD for homelessness and housing counts. The dataset is divided into two parts: Housing Inventory Count (HIC), and Point-In-Time Count (PIT) (HUD 2016). Both HIC and PIC data are collected from 2007 to 2016 across state level from Continuum of Care programs, covering virtually the whole nation.

HIC contains information about number of housing units and beds, segmented into different housing types from emergency shelters to Rapid Re-Housing – which stems from a Housing First approach. PIT Count data collects information on the number of shelter and unsheltered homeless people on a single night in January, providing a snapshot of homelessness by state. The HUD utilizes this point-in-time estimate to evaluate the change in homelessness numbers, and thus is fit for our research. Unfortunately, it was impossible to obtain a over-the-year estimate of homeless numbers by state due to confidentiality reasons (HUD 2017a) (HUD 2017b).

Through these two datasets, we obtain our outcome variable: homeless numbers in a given state and year. We also obtain our treatment variable, which is the total number of beds in Rapid Re-Housing program (RRH) in respect to the total number of beds in the Continuum of Care program in the given state, creating a continuous treatment variable for analysis. Finally, I include the shadow economy level and the interaction term between the shadow economy and the treatment variable, which is our variable of interest.

However, this simple OLS model possesses many avenues for biases and endogeneity, resulting from omitted variables, inverse causality, and measurement error. First, omitted variables such as education levels or income per capita may affect homelessness numbers in a state in a given year, as well as the state's ability to initiate and put resources into the Housing First program. Hence, due to its correlation with treatment variable, shadow economy levels, and the dependent variable, the omitted variables confound our estimates of the interaction term coefficient. Another issue specific to our research is ”measurement error” in the shadow economy levels. Since there are no reported shadow economy levels, our measurement of the shadow economy through a MIMIC model approach (which we outline in the section below) may have measurement errors that may bias the actual levels of the shadow economy, since it is correlated with both our error term and the actual level of the shadow economy. Lastly, there may be inverse causality issues between homelessness numbers and the implementation of the Housing First program. States may try to implement the Housing First program due to a rise in homelessness numbers, but also at the same time homelessness numbers are affected by states' housing policies themselves.

Correcting for such biases is difficult, but we attempt to do so through a fixed effects approach. We control for any state-level or time-level effects that may skew our estimates of the coefficients, and include other state and time variant exogenous controls such as unemployment rate, income per capita, and education level to ensure minimal omitted variables bias and suitable

Variables	N	Mean	SD	Min	Max	Description
HUD Homeless Variables						
TotalHomeless[1]	150	11,278	19,797	757	118,552	Total Homeless Numbers.
DepVar	150	8.634	1.096	6.629	11.68	Dependent variable = ln(TotalHomeless)
TotalRRHBeds[2]	150	719.4	1,096	0	6,673	Total # of Year-Round Beds in Housing First (RRH).
TotalBeds[2]	150	15,157	21,393	1,075	130,206	Total # of Beds in all housing programs.
PropBedinHF	150	0.0472	0.0405	0	0.186	Proportion of Beds in Housing First = TotalRRHBeds / TotalBeds
Control Variables						
rGDPCapita[3]	150	47,772	8,987	31,613	70,986	Real GDP per Capita.
UnempRate[4]	150	5.829	1.470	2.700	9.600	Unemployment rate.
PercHSDiploma[5]	150	89.94	3.003	82.41	95.08	Percent of aged 25-64 population with high school diploma.

Table 1: Descriptive Statistics on HUD Data and Various Control Variables.

comparison to determine the effects of the Housing First program. We also utilize homelessness numbers *within a given year* from PIC data to mitigate inverse causality, as it is difficult for state governments to change funding and policy structures to housing programs in a given year. Descriptive statistics of such variables are shown in Table 1.

Thus, after changes to the simple OLS model involving controls, fixed effects, and changes

[1] *Annual Homelessness Assessment Report*, U.S. Department of Housing and Urban Development.
[2] *Continuum of Care Housing Inventory Count Reports*, U.S. Department of Housing and Urban Development.
[3] Bureau of Economic Analysis.
[4] *Local Area Unemployment Statistics*, U.S. Bureau of Labor Statistics.
[5] *American Community Survey*, U.S. Census Bureau.

to our dependent variable, the panel regression looks as follows:

$$\ln(Y_{it}) = \beta_0 + \beta_1 H_{it} + \beta_2 U_{it} + \beta_3 H_{it} U_{it} + S_i + T_t + \sum_{k=1}^{K} \alpha_k C_k + \varepsilon_{it} \tag{1}$$

where

$$\begin{aligned}
\ln(Y_{it}) &= \text{\% change of homeless numbers in year } t \text{ in state } i \\
\beta_0 &= \text{Regression constant} \\
H_{it} &= \text{proportion of beds in RRH program in state } i \text{ in year } t \\
U_{it} &= \text{level of underground economy in state } i \text{ in year } t \\
S_i &= \text{time-invariant, state fixed effects} \\
T_t &= \text{state-invariant, time fixed effects} \\
C_k &= \text{Other control variables} \\
\varepsilon_{it} &= \text{Error term}
\end{aligned}$$

This panel regression reduces much of the endogeneity issues mentioned previously, reducing biases in estimates of our regression coefficients. The interaction term between shadow economy and the Housing First treatment variable, after controlling for omitted variable bias and reverse endogeneity that may occur with our treatment variable, becomes closer to a causal effect rather than a correlatory one. However, the issue of the measurement error of the shadow economy still remains. We can never assess the degree of the measurement error and eliminate it due to the limitations in quantifying the level of the shadow economy, and hence may still confound both the interaction term and the dependent variable. Such issues require more work to show that the interaction term is truly a causal effect. Nevertheless, we proceed with the specification of the MIMIC model which allows us to measure the shadow economy – U_{it} from the regression equation – from its observed indicator and causal factors in the next section.

4.2 Measuring the Underground Economy

We re-emphasize the issue of no official data which tracks the level of the shadow economy over time. However, I refer to the aforementioned MIMIC method in research conducted by Wiseman to measure the level of underground economy at the state level (Wiseman 2013). We define underground economy as any economic activity that deliberately evades detection by officials.

The MIMIC method consists of two parts. The first part is a structural model which relates observed variables serving as potential causes of the latent variable, with the unobserved latent variable. The second part is a measurement model which relates the correlative relationship between the unobserved latent variable and the observed indicators of the unobserved latent variable. Using these two equations, the MIMIC model assumes that the latent variable can be reconstructed from the observed variables' covariances through Maximum Likelihood Estimation (MLE). Translating the MIMIC model for our particular research problem,

$$\text{Structural:} \qquad Shadow = \psi Causals + \delta \tag{2a}$$

$$\text{Measurement:} \qquad Indicators = \gamma + \beta Shadow + \varepsilon \tag{2b}$$

where *Indicators* are observed indicators of the shadow economy, such as electricity consumption as researched by Lackó (Lackó 2000), *Shadow* is the level of the underground economy, and *Causals* are the causal factors which affect the level of the underground economy such as tax charges, regulatory activities, etc. Substitution of equations result in:

$$Indicator = \gamma + \alpha Causals + \upsilon \tag{3}$$

where $\alpha = \beta\psi$, and $\upsilon = \beta\delta + \varepsilon$. To solve this equation, it requires that model (2b) be normalized, which can be achieved by setting one element of $\beta = 1$. Then, we apply Maximum Likelihood Estimation to solve for the required coefficients ψ β, α and γ, which can then be plugged in to solve for the Structural Equation. The *Shadow* then can be interpreted as the relative level of the underground economy in terms of standard deviation away from the mean, for each state in a given year: U_{it} as seen earlier in the panel data regression equation.

We specifically utilize Indicator and Causal variables in Specification 3 detailed by Wiseman (Wiseman 2013). Descriptive statistics regarding these MIMIC method variables are shown in Table 2.

We note that data collection on Housing First program was only initiated since 2013, and hence we only have data from 2013-2016 from HUD in regards to the number of beds and units in the Housing First program. We also note that Census data does not exist for 2016 for variables related to the MIMIC method, hence limiting our dataset to 150 observations total: 3 years' worth of data across 50 states.

5 Results

5.1 MIMIC Method

We utilize the indicator and causal variables as mentioned in the section above to measure the underground economy through the MIMIC Method. The results are shown below in table 3.

Due to standardization, the coefficients in Table 3 refer to standard deviations away from the mean due to the given variable. In the left table containing the causal factors, we see that Government Expenditure and Tax Revenue were key significant factors in increasing the level of the shadow economy. For example, one standard deviation increase in tax revenue collection leads to a 0.115 standard deviation increase in the level of shadow economy, which intuitively makes sense as people may be induced to participate more in the shadow economy to evade taxes. Surprisingly, Protective Inspection and Regulation expenditure was not considered significant in determining the level of the shadow economy. We would expect that with an increase in regulation activities, the

[6] *Local Area Unemployment Statistics*, U.S. Bureau of Labor Statistics.
[7] Bureau of Economic Analysis.
[8] *Independent Statistics and Analysis*, U.S. Energy Information Administration.
[9] *State and Local Government Finances*, U.S. Department of Commerce, Census Bureau.

Variables	N	Mean	SD	Min	Max	Description
Indicators						
LFGrowth[6]	150	0.330	1.115	-3.56	3.080	Labor Force Growth Rate.
rGDPCapita[7]	150	47,772	8,987	31,613	70,986	Real GDP per Capita.
ElecPerGDP[8]	150	56.85	21.74	23.26	104.5	Electricity consumption (in millions kWh) per GDP.
Causal Variables						
CurrChargePct[9]	150	2.162	0.888	0.440	4.640	Charges & Revenue from current charges (user fees and fines) as a % of GDP.
GovtExpPct[9]	150	21.15	3.106	10.69	27.03	Government Expenditures as % of GDP.
InsureExpPct[9]	150	2.660	0.680	1.070	4.490	Insurance Trust, unemployment compensation, employee retirement, and workers' compensation expenditures as a % of GDP.
PIRPct[9]	150	0.0825	0.0368	0.010	0.230	"Protective Inspection & Regulation" expenditure as % of GDP.
TaxPct[9]	150	4.181	1.655	0.220	8.200	Indirect Tax Revenue and General and selective sales tax revenue as a % of GDP.

Table 2: Descriptive Statistics on MIMIC Method Variables.

	Causal Coeff.
Shadow	
CurrChargePct	0.0891
	(0.0585)
GovtExpPct	0.166**
	(0.0753)
InsureExpPct	0.0407
	(0.0468)
PIRPct	0.0353
	(0.0449)
TaxPct	0.115**
	(0.0519)
Observations	150

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

	Indicator Coeff.
ElecPerGDP	
Shadow	1
	(.)
Constant	-1.83e-09
	(0.0771)
LFGrowth	
Shadow	-0.185
	(0.131)
Constant	-2.04e-09
	(0.0812)
rGDPCapita	
Shadow	-1.598***
	(0.275)
Constant	3.09e-09
	(0.0686)
Observations	150

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: MIMIC Method Regression Results. Left table shows the causes and their corresponding coefficients affecting the shadow economy. Right Table shows how the shadow economy reflects on indicators such as Electricity (in millions kWh) per GDP, Labor Force Growth, and real GDP per capita. Note that electricity coefficient was set to 1 for MLE purposes of the model.

level of shadow economy would decrease; nevertheless, only government expenditure and indirect tax revenue collection percentages were considered significant.

On the other hand, the right table displays how the MIMIC model interprets the latent variable – the shadow economy – affecting the indicator variables. We see that real GDP per capita decreases significantly by 1.598 standard deviation per one standard deviation increase in the level of shadow economy increases, which matches our known assumption that underground economic activities may detract away from officially reported real GDP measures by the Bureau of Economic Analysis. Though not significant, we also see that Labor Force Growth as negatively correlated with an increase in shadow economy, as people may not officially be reported in the Labor Force due to increased participation in the shadow economy.

Using the causal variables' coefficients, we construct the level of the shadow economy through the following equation:

$$\begin{aligned} Shadow_{it} = {} & 0.0891 CurrChargePct_{it} + 0.166 GovtExpPct_{it} \\ & + 0.0407 InsureExpPct_{it} + 0.0353 PIRPct_{it} + 0.115 TaxPct_{it} \end{aligned} \tag{4}$$

Since the underlying data is standardized, the level of the shadow economy is measured in standard deviations away from the national average. For the purpose of our analyses, calculating the actual dollar amount of shadow economy market is not necessary, as the shadow economy is used as an interaction variable to see whether it affects the efficacy of our treatment variable: the proportion of beds in the Housing First Program.

5.2 Panel Regression Results

After obtaining the level of underground economy in different states in different years, I now run a panel data, state-and-time fixed effects regression. We detail regression results in Table 4.

In Table 4, we note that the first three specifications indicate regressions with no controls, on

	(1) depvar	(2) depvar	(3) depvar	(4) depvar	(5) depvar	(6) depvar
PropBedinHF	0.0781	-0.0489***	-0.0165	0.187**	-0.0307**	-0.0158
	(0.0913)	(0.0106)	(0.0139)	(0.0780)	(0.0137)	(0.0139)
Shadow	0.491	-0.0723	-0.156	0.623**	-0.129	-0.136
	(0.307)	(0.128)	(0.144)	(0.289)	(0.130)	(0.146)
PropBedinHF $\times$ shadow	-0.452	0.0538	0.0581*	-0.492	0.0565	0.0553
	(0.363)	(0.0359)	(0.0348)	(0.303)	(0.0357)	(0.0347)
Constant	8.647***	8.407***	8.494***	8.648***	8.283***	8.512***
	(0.0888)	(0.0708)	(0.0788)	(0.0734)	(0.174)	(0.181)
With Controls	No	No	No	Yes	Yes	Yes
With Time Fixed Effects	No	No	Yes	No	No	Yes
With State Fixed Effects	No	Yes	Yes	No	Yes	Yes
Observations	150	150	150	150	150	150

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Panel Data Fixed Effects Regression Results. All variables but the dependent variable are standardized.

only state fixed effects, and with both fixed effects respectively. The last three specifications are at the same varying levels of fixed effect inclusion, but also with controls such as real GDP per capita, education level, and unemployment rate.

The interaction term between proportion of Beds in Housing First and the shadow economy demonstrates the effect of shadow economy on the efficacy of Housing First program, hence our variable of interest. We see that in many of the regressions, the coefficient is deemed insignificant. The only case where we see minimal significance (at 10% significance level) is in specification 3 without controls but with both state and fixed effects. In this case, for every standard deviation increase in the level of the shadow economy, we see that the homelessness numbers are *reduced less* by 5.81%, per standard deviation increase in the proportion of beds in Housing First. This result does show that the efficacy of funding more beds into the Housing First program is reduced by the level of shadow economy, though it is minimal. One positive aspect is that except in specifications 1 and 4, where we have no state and time fixed effects, the direction of the interaction term is positive, corresponding to increases in homelessness numbers. Nevertheless, with insignificant coefficients including in our most preferred specification 6 with controls, time fixed effects, and state fixed effects, we can conclude that the shadow economy's impact on the efficacy of the Housing First program is insignificant.

Another interesting aspect of the regression is the effect of the proportion of number of beds in the Housing First program. We see that in all but specification 1 and 4 without fixed effects, the coefficient results in a reduction of homelessness number percentage. For example, specification 5 demonstrates that with a standard deviation increase in proportion of beds in Housing First results in a 3.07% reduction in homelessness numbers. However, another anomaly to note is that in specification 4, the coefficient indicated an *increase* in homelessness numbers due to the Housing First program, and was deemed significant.

Looking at the level of shadow economy variable, we again see that the coefficients were in most cases insignificant, besides specification 4 which showed a 62.3 percent increase in homelessness numbers in areas with a level of underground economy one standard deviation higher than the mean.

Overall, our panel regression results show that the level of shadow economy in a state in a given year does not affect the efficacy of the Housing First program significantly. However, in most specifications the interaction term coefficient did indicate an increase in homelessness numbers, which matches our intuition. However, in our top 2 most preferred specification with fixed effects, none but the interaction term in specification 3 were deemed significant by the panel regression fixed effects model. Furthermore, the interaction term coefficient was not robust across different specifications in terms of its significance, providing further evidence of the insignificance of the shadow economy in affecting the Housing First program.

5.3 Robustness Check: Placebo Test with Average Temperatures

Though the interaction term did not show significant coefficients in Table 4, to further test robustness I also conducted a placebo test interacting the treatment variable with average temperature instead of shadow economy in my most preferred regression of specification 6. The intuition is that when interacting the treatment variable with an unrelated term, theoretically there should be no significant effect, though the two variables may have separate effects. I chose average temperature as a candidate, because though higher temperatures may correlate with more number of homeless people as in California versus Illinois, it should have no correlation with the effect of RRH program on reducing homelessness. The results of our placebo test is shown in Table 5.

In comparison to specification 6 in Table 4, the interaction term in Table 5 also showed insignificance when interacted with average temperature. It is also interesting to note that all the coefficients of all other variables remained similar. Thus, this placebo test does indicate that when the treatment variable is interacted with a placebo, it accurately shows insignificance, implying that the insignificance of our shadow economy interaction variable in specification 6 may be robust, and true.

	(1)
	depvar
PropBedinHF	-0.0194
	(0.0143)
Shadow	-0.170
	(0.145)
PropBedinHF $\times$ AvgTemp	-0.0175
	(0.0108)
Constant	8.542***
	(0.181)
With Controls	Yes
With Time Fixed Effects	Yes
With State Fixed Effects	Yes
Observations	150

Standard errors in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Placebo Test results. All variables but the dependent variable is standardized.

6 Limitations

6.1 Calculation of Shadow Economy Levels

A limitation in the current paper is that only data from 2013-2015 is utilized to run the MIMIC model to construct the shadow economy levels. Furthermore, there may be measurement errors when utilizing the MIMIC model and incorporating it into our fixed effects regression. Due to these two factors, the regression may have resulted in unstable or biased estimates of the shadow economy due to the limited number of observations. Unfortunately finding the relevant datasets for the indicator and causal variables that Wiseman mentions was difficult and unachieveable. Hence, my current estimates of the coefficients in the MIMIC model are different in comparison to Wiseman's specification 3 which I replicated Wiseman 2013. Utilizing more years' worth of data to construct a more robust MIMIC model and hence also shadow economy levels would be necessary for the future, as we hypothesize shadow economy levels as critical in determining the efficacy of the Housing First program.

6.2 Limited Housing First Dataset

Another limitation that is in nature similar, but involves a completely different dataset is the insufficiency of data in the Housing First program. Across all 50 states, the U.S. Department of Housing and Urban Development only started collecting data in regards to Housing First starting 2013, providing a very limited dataset to work with in looking at the efficacy of the Housing First program. Resolving such an issue is difficult as we cannot control HUD's data collection procedure and ask for past data. Instead, we could also look at other Housing programs that has been implemented for a longer period of time, and see its efficacy while also considering for the level of the shadow economy.

7 Conclusion

In this research paper, we sought to analyze how the shadow economy affects the efficacy of the Housing First program in reducing homelessness numbers. Preexisting literature had shown general positive effects of the Housing First program in both Canada and United States. Simultaneously however, substance abuse and other activities related to the shadow economy have also been shown to de-motivate and negatively impact the homeless, providing it difficult for people to escape homelessness. In connecting the two aspects – policy and homelessness-related negative activities such as substance abuse – we explored how the shadow economy, which facilitates negative actions among the homeless, may reduce the impact the efficacy of the Housing First program.

Though difficult to quantify and never officially reported, we first utilized the Multiple Indicators and Multiple Causes method (MIMIC) to measure the level of the shadow economy in a state in a given year. The MIMIC method utilized maximum likelihood estimation to reconstruct the shadow economy through the covariances of causal variables such as increased tax collection and indicator variables such as electricity consumption. Constructing the MIMIC model required data from various sources such as the Census Bureau, Bureau of Economic Analysis, Bureau of Labor Statistics, Energy Administration, among others.

After obtaining the standardized level of the shadow economy, we ran a fixed effects panel regression model, controlling for time variant and state variant controls, as well as state and time fixed effects. Our treatment variable was the proportion of beds in the Housing First program, with our dependent variable as the natural log of the total homelessness numbers on the state-year level, to provide percentage interpretations of coefficients. Our variable of interest was the interaction term between our treatment variable and the shadow economy levels, which measured the impact of shadow economy on the efficacy of Housing First program in reducing homelessness numbers.

Regression results showed little to no significance in shadow economy's impact on the Hosing First program, with the interaction term only being significant at the 10% significance level in one of the six specifications, which involved time and state fixed effects but no controls. In this specification, results showed that a state in a given year with a street economy above a full standard deviation would only result in reduced efficacy of 5.81% in reducing homelessness numbers, when including a full standard deviation more proportion of beds into the Housing First program. A placebo test by interacting the treatment variable with average temperature in our most preferred specification showed that the placebo interaction was insignificant.

For further research, obtaining a larger dataset that consists more than 3 years' worth of data will be paramount to creating more robust estimates of both shadow economy levels and regression coefficients. Another critical issue is that the U.S. Department of Housing and Urban Development only possess data on the Housing First program starting 2013, which limits our panel regression dataset. Though it is difficult to solve such an issue, perhaps a more specific dependent variable regarding chronic homelessness and specifically limiting to long-run or short-run effects of the Housing First program may provide new avenues for research.

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