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How does female labor force participation impact on housing values?

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ABSTRACT

Female labor force participation (FLFP) and household wealth are two main topics of interests to economists for long time. The objective of this study is to investigate the response of housing values, household wealth, to female labor force participation using panel level data in the U.S. states. We develop static and dynamic estimation models using state-level data in the U.S. from 2005 to 2013. The results show the FLFP rate and per capita income have a strong positive effect on housing values, while the number of units per capita has a negative effect on housing values in the state. We find that a 10% increase in FLFP will result in an increase of about 12.5% on housing values. Additionally, increasing per capita income by 10% on average will cause housing values to rise by 9%, however, a 10% rise in the number of units per capita will decrease housing values by 30%. The results assist economists and policy makers in assessing policies to optimize decisions in labor market and housing market.

1. Introduction

Economic outcomes have experienced substantial changes over the past decades in many countries. Two notable changes including Female Labor Force Participation (FLFP) and household wealth in most countries, specifically in the U.S. FLFP is the main factor in the production function and economic outcome (Cavalcanti and Tavares, 2008; Cubas, 2016), while housing values show wealth of households (Lusardi and Mitchell, 2007; Skinner, 1989). Most homeowners believe their house could be the most important consumption good and asset at the same time in their portfolio (Flavin and Yamashita, 2002). Also, housing wealth could be the predominant non-pension investment vehicle for saving the money (Begley and Chan, 2018). Thus, understanding the main variables that impact on FLFP and housing values are important for most economists and policymakers. FLFP and housing prices change over past decades simultaneously as seen in Fig. 1. This figure shows the relationship between FLFP and Housing Price Index (HPI) for the U.S. states in 2017. This trend shows positive correlation exists between FLFP and housing prices, which indicates housing values relate to FLFP. Thus, increasing women decisions to work may resulted to increase housing prices as well.

This study investigates to the direction of causation between housing prices and FLFP using the state-level data in the U.S. There are three main possible scenarios for this observation. First scenario, high house prices encourage women to

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Fig. 1. Trend between FLFP and HPI for U.S. states in 2017.

work and contribute their income regarding their households' expenditures, so more women tend to work to have their own desire houses, so housing prices affect on FLFP. Second scenario, those families who have two earners could pay more to their houses, so this resulted to bid up the price of desire houses which raising the relative price of housing. This scenario indicates that increasing FLFP impacts positively on housing prices. Third scenario, there is an omitted variable which has correlation with both housing price and FLFP and there is no causation exist between housing market and labor market (Johnson, 2014). To overcome to omitted variable issue, this study suggests to run different specific estimation models to validate the results.

Finding the relationship between FLFP and housing values based on the first theory (scenario) has been considered by several studies. Generally, studies that employ first theory, housing values affect on women decisions to work, suggest that policy makers can estimate women's decisions to work due to their housing values. Holtz-Eakin et al. (1993) examine the effect of receiving inheritance on the labor force participation behavior in the U.S. They conclude that large inheritances decrease a person's labor force participation and the likelihood of an individual decreases his/her labor force participation depends on the size of the received inheritance (Douglas Holtz-Eakin, 1993). Henley (2004) investigates an individual's hours of work resulted from amount of housing wealth capital gain using British panel data. He concludes that housing gains reduce working hours for both men and women in response asymmetric whereas men appear to increase hours in response to housing losses, while women reduce hours in response to housing gains (Henley, 2004). Black et al. (2014) indicate that FLFP of married women are negatively affected by commuting time, so metropolitan areas with larger community time had experienced slower growth in FLFP (Black et al., 2014). Fu et al. (2016) employs China household survey data to estimate the effect of changes in housing values on labor force participation. They show that a 100,000 yuan increase in housing values results to a 1.37 percent decrease in FLFP (Fu et al., 2016). Additionally, Zhao and Burge (2017) investigate the relationship between housing values, property taxes, and labor supply. They show changes in housing values impact on labor supply as well as changes in financial assets and work in the same direction (Zhao and Burge, 2017).

Second theory suggests more women into labor market resulted raising household incomes and setting off a bidding war for their housings that causes increasing housing prices. Fortin (1995) employs empirical evidence to shows mortgage commitments impact on the decisions of married women regarding the job. She concluded that if outstanding mortgage amount of the average household decreases, the FLFP would be decrease respectively (Nicole M. Fortin, 1995). Green and Hendershott (2001) find a positive relationship between a country's unemployment rate and the rate of home-ownership (Bloze and Skak, 2016; Green and Hendershott, 2001). Haurin et al. (1996) show the wealth accumulation of American youth related to their housing choices and indicate women working hours are positively related to houses prices (Haurin et al., 1996). Jacob and Ludwig (2012) employs data from a randomized housing voucher in Chicago to examine the effect of housing assistance on labor supply. They show that housing vouchers reduce labor force participation and they find no evidence of housing-specific mechanism to promote work (Jacob and Ludwig, 2012). Johnson (2014) indicates that house prices are unlikely to raise FLFP, while it may affect on earnings. Likewise, an instrument for married women's labor supply reveals no casual effect of two earner households on housing values (Johnson, 2014). The large numbers of female who motivated to work within a concentrated geographic area provide more positive growth in externalities, which may cause increase house values. Households whose both husband and wife have a college education have been increasing and they tend to locate in larger metropolitan area to find their proper jobs (Costa and Kahn, 2000).

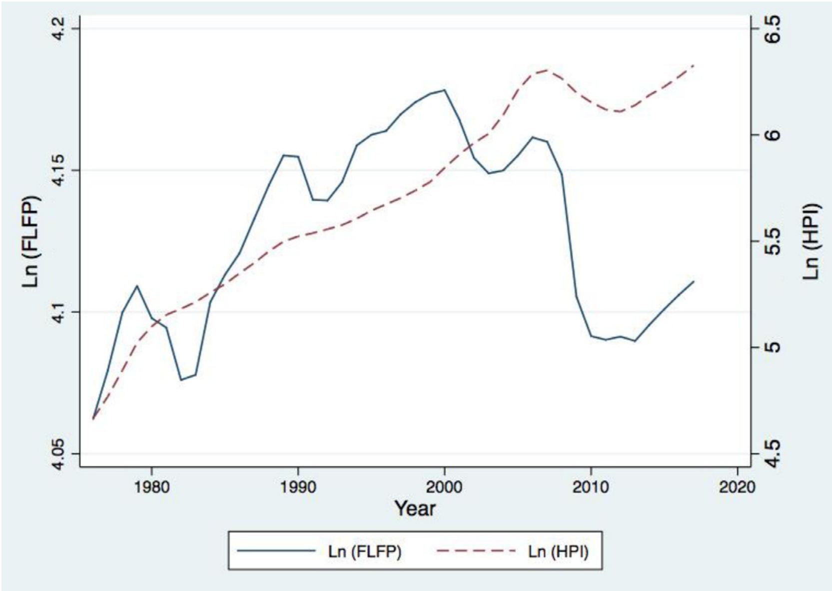

Fig. 2. Trend of FLFP and HPI from 1976 to 2017.

Housing is the main component of household's wealth and long-term investment in most countries, particularly in the U.S. Moreover, those households whose women work may have more opportunity to buy more expensive houses. In the United States, homeowners have equity more than 57 percent of the total value of household real estate ("Board of Governors of the Federal Reserve System (US), Households; Owners' Equity in Real Estate as a Percentage of Household Real Estate, Level [HOEREPHRE], retrieved from FRED," 2018). United States has been experiencing an extensive housing price appreciation recently. The FLFP and housing values differ from state to state because every state has different characteristics, socio-demographics, and regulations. Furthermore, many states have a higher population and income rather than some countries. Thus, understanding the main factors that impact on FLFP and housing values and find the relationship between these variables are important for policy makers.

To make clarification about this relationship between FLFP and housing values, this study uses FLFP and Housing Price Index (HPI) data and shows the trend in Fig. 2. This figure shows how FLFP and HPI move from 1976 to 2017. Fig. 2 indicates that FLFP and HPI move together while FLFP is superior in the direction. Remarkably, this pattern shows that FLFP may impact on HPI since it moves superior compared to the HPI. Thus, this study suggests that using FLFP as an explanatory variable to estimate HPI rather than dependent variable since FLFP may affect on HPI.

This study differs from previous from two main aspects. First, this study uses macro level data (state-level) rather than micro level data (individual) to estimate the effect of FLFP on housing values in the U.S. This is the first study using macro level data in the U.S. to estimate the effect of FLFP on housing values at the state-level. Second, this study uses static and dynamic estimation models and various robustness tests to address possible measurement errors including causation issues.

The rest of the paper is organized as follows: Section 2 provides datasets; Section 3 describes methodology approaches for both static and dynamic estimation models; Section 4 shows the empirical results; Section 5 presents the conclusion.

2. Data

This study uses annual U.S. data for 48 states from 2005 to 2013. Hawaii, Alaska, and Washington, D.C. excluded from the main sample since their complete data sets were not available. This period is the longest period of time that data for all variables are available. FLFP data at the state-level provide by the Bureau of Labor Statistics (BLS). This study obtains HPI at the state-level from Federal Reserve Bank of St. Louis ("Board of Governors of the Federal Reserve System (US), Households; Owners' Equity in Real Estate as a Percentage of Household Real Estate, Level [HOEREPHRE], retrieved from FRED," 2018). Additionally, socio-economic and demographic characteristics at the state level are collected from the American Community Survey (ACS). Table 1 presents summary of variables and descriptive statistics from 2005 to 2013.

Also, Table A1 reports summary of variables for each state from 2005 to 2013.

3. Methodology

This study uses statistics and dynamic estimation models to estimate housing wealth at the state-level. The statistic estimation models are various ordinary least squares (OLS) models with different specification, while the dynamic estimation models are different generalized method of moments (GMM) estimators.

Table 1
Summary of variables and descriptive statistics from 2005 to 2013.

Variables	Mean	Std. dev.	Min	Max
Per capita income	25,923.59	3881.67	17,971.3	37,725.52
Educational level*	0.37	0.04	0.27	0.46
Number of units per capita	0.44	0.31	0.34	0.57
FLFP	61.6	4.74	50	72
HPI	194.86	34.42	119.43	316.08

* Percentage of people that have at least a high school degree.

Table 2
Variance inflation factors (VIFs) for all variables.

Explanatory variables	VIF	1/VIF
Educational level	2.26	0.441
LN per capita income	2.23	0.449
LN FLFP	1.21	0.829
Number of units per capita	1.08	0.9264
Mean VIF	1.69	

This study uses a set of static panel estimation models to examine the effect of various independent variables to estimate HPI. There are many independent variables that may impact on housing values, so this study employs those main variables, which are supported by previous studies, and their data are available at the state-level.

Including all possible variables may result in a multicollinearity issues in the model. This study uses a variance inflation factor (VIF) to overcome to the multicollinarity issues, which may exist among explanatory variables. Table 2 presents the VIF values of explanatory variables for estimation models. The higher the value of the VIF, the higher the collinearity is existed between selected variables. The value of the VIFs are less than 5, which indicates that multicollinearity among the explanatory variables is not a problem and there is no significant correlation exist among explanatory variables (Javid et al., 2017; Salari and Javid, 2017).

Therefore, this study uses the following static model to estimate FLFP across states.

$$HPI_i = \alpha + \beta_i \ FLFP_i + \lambda' X_i + \varepsilon_i \tag{1}$$

where as the dependent variable HPI_i is housing price index at state i, while $FLFP_i$ is a percentage of married women who are in the job markets over the total married women at state i. α is a constant number, and ε_i is the error term. X_i represents control variables including state-level variables that may impact on HPI. Explanatory variables include per capita income, number of units/houses per capita, and educational level.

This study employs several statistic models regarding state-specific effects to find the best statistic estimation model. Cross-section pooled OLS model is used when there is no state-specific effects exist. Then, this study uses Generalized Least Squares (GLS) model while employing Random Effect (RE), Fixed Effect (FE), and panel corrected standard error model estimators. Also, this study uses dynamic panel estimation models to estimate FLFP at state-level over time. The FLFP is estimated by using the system GMM estimator (GMM-BB) (Blundell and Bond, 1998) and (GMM-AB) (Arellano and Bond, 1991), while GMM-BB estimators are superior to other dynamic estimators. This study uses the following dynamic model to estimate FLFP at state-level.

$$HPI_{it} = \alpha + \beta_1 \ HPI_{it-1} + \beta_2 \ FLFP_{it} + \lambda' X_{it} + \varepsilon_{it} \tag{2}$$

The GMM estimator models can be one-step system GMM models and two-step GMM models. The one-step models assume independent error terms and homoscedastic error variances across states and times, while two-step system GMM models use residuals of the first-step estimation to estimate the variance-covariance matrix when there is no assumption about independency and homoscedasticity (Salari and Javid, 2016).

4. Results

This section presents the empirical results of different estimation models. Table 3 represents the static model including OLS with different specification in the model. In the first column, the estimated coefficient measures the effect of FLFP on HPI. Column 2 includes state fixed effect on the model to estimate the effect of FLFP on HPI, while column 3 includes both state fixed effect and year fixed effect on the model. The findings show that in all models FLFP has statistically positive effect on HPI. Column 4, column 5, and column 6 use all explanatory variables while employing different specification models. In all models, FLFP has positive impact on housing wealth at the state-level. This finding indicates that in those states whose women have more tend to work, their families can bid up on housing prices and the housing values increase compared to

Table 3
OLS regression models with different specifications.

	(1)	(2)	(3)	(4)	(5)	(6)
LN FLFP	1.082***	1.916***	2.434***	0.249*	1.256***	0.503**
	(0.170)	(0.101)	(0.232)	(0.143)	(0.176)	(0.237)
LN per capita income				0.931***	0.965***	1.942***
				(0.104)	(0125)	(0.159)
Number of units per capita				−1.597***	−3.123***	−4.486
				(0.335)	(0.599)	(0.582)
Educational level				1.214***	−3.639***	0.461
				(0.394)	(0.610)	(0.714)
Constant	1.674**	−1.861***	−4.019***	−4.105***	−6.228***	−13.570***
	(0.701)	(0.408)	(0.939)	(1.115)	(1.080)	(1.272)
State fixed effects	No	Yes	Yes	No	Yes	Yes
Year fixed effects	No	No	Yes	No	No	Yes
R-square	0.086	0.939	0.950	0.466	0.955	0.968
N	432	432	432	432	432	432

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

Table 4
OLS regression models with different specifications.

	(1)	(2)	(3)	(4)
LN FLFP	2.434***		0.502**	
	(0.232)		(0.237)	
Lagged Ln FLFP		2.369***		0.435*
		(0.228)		(0.232)
LN per capita income			1.942***	1.969***
			(0.159)	(0.159)
Number of units per capita			−4.486***	−4.469***
			(0.582)	(0.583)
Educational level			0.462	0.415
			(0.714)	(0.713)
Constant	−4.019***	−3.751***	−13.569***	−13.553***
	(0.939)	(0.000)	(1.272)	(1.273)
State fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
R-square	0.950	0.949	0.968	0.968
N	432	432	432	432

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.

other states. Other explanatory variables mostly are statistically significant and their signs are consistent with the previous studies. The findings indicate that per capita income has positive impact on housing values, so one would expect than an increasing/decreasing on per capita income in a given state resulted to increasing/decreasing housing prices in that state. Moreover, the number of units/houses per capita has negative impact on house values. The housing wealth will decrease since the buyers have more opportunity to select among existed units/houses. So, those states with higher units/houses per capita have more supply of units/houses than other states and the housing prices are decreased compared to other states.

It is possible to argue that the housing values are affected by the FLFP of previous years. Table 4 presents the results for the different years of FLFP (current year of FLFP and one year Lagged FLFP) to show how HPI related to the FLFP. The results show that FLFP of one year before is good substitute for FLFP of a given year and both can be used interchangeably, while for estimating HPI, FLFP of a given year give us slightly better estimation model rather than FLFP of a one year before.[1] So, the results confirm that the FLFP of a given year is best estimator of HPI at the given year compared to other years of FLFP.

The results of the static models are presented in Table 5 for estimating HPI. All explanatory variables are statistically significant and the coefficients display the expected signs. Column 1 shows estimating housing values at the state-level

[1] This study uses the two years lagged FLFP, and three years lagged FLFP as well to pick the best year of FLFP to estimate HPI.

Table 5
Static models to estimate housing values.

Variables	Pooled OLS	Random effect	Fixed effect	Panel corrected standard error
LN FLFP	0.249*	1.532***	1.256***	1.256***
	(0.143)	(0.136)	(0.176)	(0.312)
LN per capita income	0.931***	0.903***	0.965***	0.965***
	(0.104)	(0.113)	(0.125)	(0.193)
Number of units per capita	−1.597***	−2.595***	−3.123***	−3.123***
	(0.335)	(0.506)	(0.599)	(1.078)
Educational level	1.214***	−2.485***	−3.639***	−3.639***
	(0.394)	(0.473)	(0.610)	(0.653)
Constant	−4.105***	−7.280***	−6.106***	−6.106***
	(1.115)	(1.056)	(1.082)	(2.556)
Observations	432	432	432	432
R-square	0.466	0.615	0.622	0.622
Bruschen-Pagan LM test		756.72***		
		(0.000)		
Hausman specification test			30.35***	
			(0.000)	
Heteroskedasticity test				1931.88***
				(0.000)
Wooldridge test				438.565***
				(0.000)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

while using cross-section pooled OLS based on all explanatory variables. The findings indicate that all explanatory variables in column 1 are statistically significant. The results show that FLFP, per capita income, and educational level have positive effect on housing values while the number of units per capita has negative effect on housing values. Similarly, column 2 accounts for unobserved heterogeneity by using RE for state-specific effects in the model. The results also indicate that all variables in the RE model are statistically significant at the 1% level. This study uses Bruschen-Pagan LM test to select between cross-section pooled OLS or RE models. The Bruschen-Pagan LM test shows that the RE model is more appropriate than the cross-section pooled OLS for estimating housing values. Column 3 uses the FE for state-specific effects in the model, while this study employs Hausman specification test to compare the FE and RE models. This test indicates that the FE estimation model is more robust than the RE estimation model, so the this result suggests to use FE estimation model compared to RE estimation model. Finally, the heteroskedasticity and Wooldridge tests indicate that the residuals in the FE estimation model are serially correlated. So, this study using the panel corrected standard error estimator in column 4 to estimate housing values. Thus, our tests indicate that the best static model is the panel corrected standard error, which presents in column 4.

Generally, the results indicate that the that FLFP and per capita income have positive impact on determining housing values while the educational level and the number of units per capita have negative impact on housing values.

The results indicate that a 1% increase in FLFP will result in an increase of about 1.25% on housing values. Additionally, increasing per capita by 1% on average will cause housing values to rise by 0.9%. On the other hand, a 1% rise in the number of units/houses per capita will decrease housing values by 3%.

Static panel estimation models may not appropriate for panel data. So, using dynamic panel estimation models are more accurate than static ones for estimating housing values over time. Additionally, adding a lagged dependent variable in the explanatory variables to estimate housing values violates the strict exogeneity assumption in the static models. So, this study employs the lagged dependent variable in the explanatory variables in the dynamic models. Table 6 presents the dynamic estimation models for estimation housing values.

This study uses the one-step system GMM estimator, including one period lagged dependent variable. To test the over identifying restrictions imposed by using the one-step system GMM estimator, this study uses the Sargan test. The Sargan test indicates that the null hypothesis is rejected in the one-step system GMM model. Thus, this study concludes that the one-step system GMM estimation model may not be appropriate for estimating housing values. Thus, two-step dynamic GMM model is used to estimate housing values at the state level. The Sargan test indicates that the two-step dynamic model is valid, and the Arellano-Bond tests for autocorrelation indicates that in the two-step dynamic model there is no significant second-order autocorrelation. Two-step system GMM estimation is a robust and unbiased estimator compared to one-step system GMM estimator. The results indicate that the one period lagged dependent variable is statistically significant at the 1% level. The results of dynamic models are consistent with the findings of static models regarding the signs of explanatory variables.

Table 6
Results of dynamic panel estimations for housing values.

Variables	One-step dynamic GMM	Two-step dynamic GMM
Lagged Ln HPI	0.411***	0.418***
	(0.019)	(0.013)
LN FLFP	1.159***	1.141***
	(0.089)	(0.042)
LN per capita income	0.164**	0.159***
	(0.072)	(0.019)
Number of units per capita	−3.001***	−3.025***
	(0.393)	(0.166)
Educational level	−1.122***	−1.089***
	(0.331)	(0.103)
Constant	−1.088**	−1.012***
	(0.538)	(0170)
Observations	336	336
Wald chi-square	4041.09***	11,452.99***
	(0.000)	(0.000)
Sargan test	247.273***	45.355**
	(0.000)	(0.015)
Arellano-Bond test for AR(1)		2.443**
		(0.015)
Arellano-Bond test for AR(2)		−2.140**
		(0.032)

*Significant at the 10% level.
**Significant at the 5% level.
***Significant at the 1% level.

The results of this study are not quite comparable to the other studies due to its unique data sets and different static and dynamic approaches.

5. Conclusion

Generally, there are two main theories exist for the relation between housing market and FLFP. First theory indicates that FLFP are a function of housing values while second theory suggests that the housing values are a function of FLFP. This study indicates that the relationship between housing values and FLFP are strongly positive while FLFP just move before housing values in the same direction, which shows FLFP may affect on housing values. This study uses different static and dynamic estimation models to estimate housing values based on various explanatory variables and specifically the FLFP at the state-level in the U.S. Therefore, this study uses aggregated panel data for 48 states in the U.S. over 9 years. Panel corrected standard error estimator is chosen as the better estimator compared to the pooled OLS, FE, and RE estimator models in static estimation models. Moreover, the two-step system GMM estimator is more desirable than one-system GMM estimator. Overall, the results of static and dynamic approaches are consistent regarding explanatory variables to estimate housing values. The findings indicate that higher/lower FLFP and per capita income are related with higher/lower housing values respectively, while the higher/lower educational level and the number of units/houses per capita are related with lower/higher housing values. We find that a 10% increase in FLFP will result in an increase of about 12.5% on housing values. Additionally, increasing per capita income by 10% on average will cause housing values to rise by 9%, however, a 10% rise in the number of units per capita will decrease housing values by 30%. Generally, the FLFP and per capita income have positive impact on housing values, while educational level and the number of units/houses per capita have negative impact on housing values.

These findings could be used by state or national policy makers to optimize their decisions regarding the two main economic variables including FLFP and housing wealth. The results assist economists and policy makers in assessing policies to optimize decisions in labor market and housing market.

Conflict of interest

We have no conflicts of interest to declare.

Supplementary material

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.rie.2019.03.002.

Appendix A

Table A1
Summary of variables for each state from 2005 to 2013.

States	HPI	FLFP	Ln per capita income	Number of units per capita	Educational level
Alabama	342.48	55.63	10.02	0.459	0.334
Arizona	504.83	58.30	10.10	0.431	0.384
Arkansas	351.83	57.44	9.94	0.453	0.311
California	925.96	59.04	10.24	0.364	0.381
Colorado	561.72	66.34	10.28	0.436	0.438
Connecticut	600.55	63.02	10.49	0.414	0.409
Delaware	504.42	60.31	10.25	0.450	0.368
Florida	437.18	57.74	10.14	0.474	0.382
Georgia	346.65	60.87	10.10	0.417	0.349
Idaho	416.14	62.30	9.98	0.422	0.377
Illinois	442.28	61.68	10.24	0.410	0.384
Indiana	352.90	60.33	10.07	0.435	0.330
Iowa	359.06	67.78	10.13	0.443	0.373
Kansas	338.02	66.11	10.14	0.436	0.393
Kentucky	391.30	56.80	10.00	0.447	0.318
Louisiana	400.83	57.16	10.02	0.433	0.302
Maine	547.13	61.44	10.13	0.537	0.390
Maryland	638.47	64.53	10.43	0.411	0.413
Massachusetts	796.39	61.97	10.41	0.424	0.424
Michigan	385.42	56.99	10.11	0.455	0.378
Minnesota	501.80	67.73	10.28	0.443	0.424
Mississippi	305.54	54.28	9.87	0.431	0.314
Missouri	378.34	61.57	10.09	0.452	0.360
Montana	557.84	61.89	10.06	0.470	0.408
Nebraska	364.60	69.64	10.12	0.438	0.394
Nevada	493.30	60.99	10.16	0.430	0.360
New Hampshire	584.45	66.93	10.34	0.459	0.421
New Jersey	711.36	61.53	10.43	0.403	0.392
New Mexico	471.53	57.46	10.01	0.437	0.360
New York	622.98	58.17	10.32	0.414	0.382
North Carolina	404.35	59.11	10.09	0.454	0.369
North Dakota	368.91	70.71	10.18	0.480	0.404
Ohio	342.80	60.63	10.11	0.443	0.349
Oklahoma	349.60	59.80	10.02	0.447	0.346
Oregon	650.46	59.64	10.14	0.432	0.430
Pennsylvania	459.91	59.89	10.19	0.440	0.342
Rhode Island	695.59	61.58	10.25	0.434	0.380
South Carolina	385.09	56.44	10.03	0.459	0.348
South Dakota	399.06	68.94	10.07	0.448	0.371
Tennessee	373.40	58.24	10.05	0.443	0.333
Texas	345.72	61.87	10.09	0.394	0.337
Utah	523.71	66.31	10.02	0.350	0.375
Vermont	541.34	66.93	10.21	0.509	0.409
Virginia	556.45	64.60	10.36	0.422	0.406
Washington	749.63	61.98	10.27	0.425	0.437
West Virginia	290.28	51.68	9.96	0.483	0.290
Wisconsin	432.43	65.32	10.17	0.459	0.374
Wyoming	492.85	67.24	10.20	0.464	0.401

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