The Proliferation of Dollar General in Distressed Communities: A Spotlight Analysis in Virginia

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1 Summary

There is growing concern that low-priced budget stores, like Dollar General, contribute to the decline of economic prosperity in areas that are already poverty-stricken. Ostensibly, increased access to affordable food and other essential items seems beneficial to cities suffering from rising poverty rates and inequality. However, some evidence suggests that the pervasive spread of dollar stores in low-income areas contributes to economic decline in such regions. By saturating already impoverished areas with low-cost dollar stores, the development of large-scale grocery chains in such locations is less attractive for major grocery retailers. Thus, communities are confined to the budget-option for food and other necessary goods. This analysis seeks to evaluate if declining economic measures explain where Dollar General targets its stores, with a focus on counties in Virginia.

2 Research Question

Do declining economic factors explain the proliferation of Dollar General stores in certain counties in Virginia? I hypothesize that Dollar General targets counties with higher poverty rates, lower incomes, and diminishing labor force.

3 Background

Dollar General is an affordable small-box grocery store that offers a range of foods, snacks, cleaning supplies, basic housewares, beauty items, as well as some basic apparel and seasonal items. As of January 31, 2020, Dollar General operates 16,278 stores across forty-four states, with the bulk of its stores located in America's southern region. Currently in Virginia, there are almost 450 stores spanning the state's 95 counties and 38 independent cities. (Dollar General Corporation, 2019).

One of Dollar General's key operating strategies has been to capitalize on a low-risk real estate growth model, as stated in the corporation's 2019 annual report. Unique to Dollar General, this strategy involves obtaining a vast amount of smaller scale stores, usually less than 10,000 square feet, in convenient neighborhood locations. This strategy "helps drive trip frequency," and makes Dollar General "an attractive alternative to large discount and other large-box retail and grocery stores." (Dollar General Corporation, 2019). Dollar General has continued this approach since its formation in 1939, giving the corporation a distinctive advantage of market share.

Still, despite Dollar General's intention to provide a wide range of essential goods to under-served communities, the overall benefit to such communities is debated. Some data indicate that target locations for new Dollar General stores tend to be in communities already experiencing economic distress. Research by the Institute for Local Self-Reliance suggests that dollar stores tend to prey on "areas with few or no grocery stores," as well as "African American neighborhoods." (Institute for Local Self Reliance, 2018).

The objective of this analysis is to determine if declining economic variables create attractive locations for new Dollar General stores. I compare poverty rates, income levels, and labor force size across every county and independent city in Virginia. Labor force size is used as a proxy for population density, simply due to the ease of accessing such data.

4 Data Sources

Location data for each Dollar General store in Virginia was obtained by web-scraping the Dollar General Store Locator web page. The output was a JavaScript Object Notation (JSON) file. I wrote a function in Python that "flattens" the nested structure of a JSON file, and applied it to the location data. The location data was then converted from a JSON file to a Comma Separated Values (CSV) file. This file provided not only the address for each Dollar General in Virginia, but also the opening date of each store.

Since this analysis focuses on county level data, each address required its corresponding county. First, I matched each city name in the scraped location data with the appropriate FIPS code issued by the American National Standards Institute. Then I matched each FIPS code to its designated county in Virginia using the US Census Bureau's 2019 FIPS Code data. From here, I created a data frame with *year*, *county*, and Dollar General *count* (in each year) as columns.

Poverty rates and median income data were extracted from the Small Area Income and Poverty Estimates (SAIPE) State and County Estimates for years 1999 through 2018. All median dollar amounts from each year were converted into 2018 dollars using the Bureau of Labor Statistics' (BLS) Consumer Price Index for all Urban Consumers Research Series for all items.

Obtaining labor force information per county per year proved to be the most challenging obstacle of data collection. Historical labor force participation rates (and naturally unemployment rates) at the county level were not readily available. To create this data, I initiated a data frame consisting of only the Local Area Unemployment Statistics (LAUS) codes for each county in Virginia. The reason for this will become apparent after later describing a "for" statement . These codes are from the Bureau of Labor Statistics' LAUS Labor Force Data by county for 2018. The resulting data frame included only *county* and *LAUS area code*, which are in the format "CN5100100000000" (using Accomack County as an example). Adding two values to the end of the LAUS series identifier will give desired measure codes. Using this data frame with each LAUS area code, two new columns were created adding '05' for employment size and '06' for labor force. Below is an example of this new dataframe.

Table 1: Preview of *laus* Data Frame

name	emp	lf
Accomack County	LAUCN510010000000005	LAUCN510010000000006
Amherst County	LAUCN510090000000005	LAUCN510090000000006
Appomattox County	LAUCN510110000000005	LAUCN510110000000005

Using the *laus* data frame, previewed above, along with a python library for the BLS application programming interface (API), the code preview on the next page produced the final data frame that will be used throughout this paper.

5 Treatment

Economic decline or growth in a county can be roughly determined by its poverty, household incomes, and labor force trends. The initial observations will consider Virginia as a whole, with the goal of detecting any relation between economic decline (high poverty rates, low incomes, low labor force participation), and the growing number of Dollar General stores.

After understanding the outlook of Dollar General in the entire state, it is important to then determine which counties in Virginia have the highest number of Dollar General stores. If these counties also have poverty rates trending upward over the last two decades, as an example example, this could offer a clue towards explaining the occurrences of new Dollar General stores locating in such counties.

Following data exploration, I will build a regression model to understand the impacts, if any, that poverty rates, income levels, and employment have on the total number of Dollar General stores in a particulate county.

6 Exploratory Data Analysis

Virginia has had a steady increase of new Dollar General stores since the first store opened in 1962. After the 2008 recession, the corporation has added on average about nineteen new stores in Virginia per year. In 2017, a record of thirty new stores opened throughout the state, coinciding with Dollar General's long-term goal to be a convenient and attractive alternative to other grocery retailers. Figure 1 shows the growth of Dollar General in Virginia since 1962.

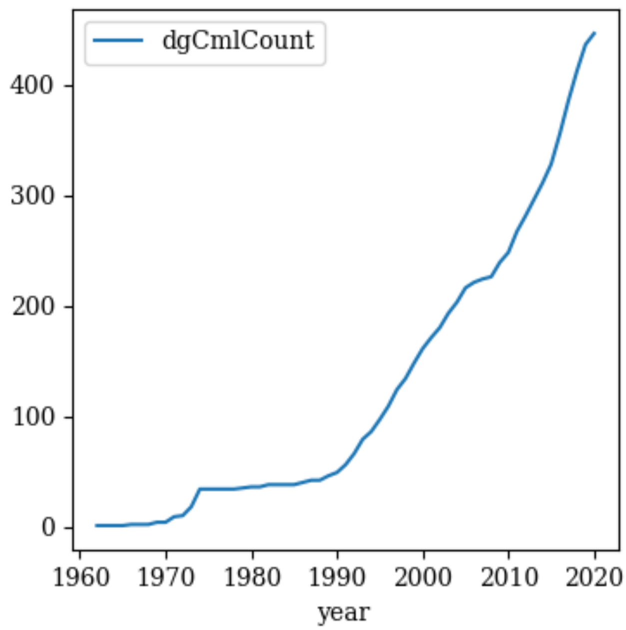

Figure 1: Cumulative Dollar General Count in Virginia

While cleaning the missing values in the completed data frame, it became apparent that in 2014, Bedford city "changed its legal status to town, ending its independent city status (county equivalent), and was absorbed as a municipality within Bedford County, Virginia." (U.S. Census Bureau, 2014). The status change of Bedford city is reflected in this analysis by absorbing all three counts of Bedford city Dollar Generals into Bedford County. It is worth noting that the population of Bedford city alone in 2013 was around 6300 people.

An interesting variable found in the original web-scraped location data was a dummy variable named "multicultural hair." Initially, this variable seemed to be some evidence that Dollar General targets African-American communities. However, further inspection revealed that 'multicultural hair' is a filterable item that users on the Store Locator web page may select in order to find a Dollar General store that sells multicultural hair products. Among the other filterable items are: Western Union, Redbox, AmeriGas, and RugDoctor. These are items or services that Dollar General can provide to its customers.

Richmond city holds the largest number of Dollar Generals in Virginia, with thirteen stores spanning its sixty-three square miles. Richmond city also has one of Virginia's highest poverty rates, at 22.3 per cent in 2018. Though the highest poverty rate for the state belongs to Radford city, at 30.4 per cent in 2018, where only two Dollar General stores reside. Table 2 shows 2018 statistics for the counties with the most Dollar General stores.

Table 2: Counties with Most Dollar General Stores in Virginia

County	DG Count	Poverty Rate	Real Median Income	Labor Force
Richmond city	13	22.3	48,747	17,577
Bedford County	11	10.1	61,186	38,270
Henry County	7	20.0	68,471	23,672
Norfolk city	7	19.7	48,519	111,338
Franklin County	6	15.3	53,522	26,182
Virginia Beach city	6	7.5	76,520	232,337

From Table 2, it is hard to discern a clear pattern among the counties with the most Dollar Generals. Poverty rates seem to be fairly high, with the exception of Virginia Beach city. Also the size of the labor forces for the counties in Table 2 are relatively small, not counting Virginia Beach city and Norfolk city. Further analysis between the variables is required. Observing the pairwise correlation matrix from Table 3, it appears that the count of Dollar Generals may be related to the percentage change of the size of the labor force. Other relations which are intuitive appear: poverty rate is strongly and negatively related to median incomes, labor force participation rate is positively related with median incomes, etc. Because of how strongly correlated poverty rate is with median incomes, one of these variables could cause multicollinearity issue in the linear regression model.

Table 3: Pairwise Correlation Matrix

	dgCount	povPcnt	realMedInc	lfPartRate	lf_size	logMedInc	logLf_size
dgCount	1.000000	0.098851	-0.119284	-0.031421	0.173329	-0.093381	0.423217
povPcnt	0.098851	1.000000	-0.809335	-0.739640	-0.283034	-0.857862	-0.360101
realMedInc	-0.119284	-0.809335	1.000000	0.656484	0.527488	0.985048	0.557318
lfPartRate	-0.031421	-0.739640	0.656484	1.000000	0.252061	0.704889	0.313625
lf_size	0.173329	-0.283034	0.527488	0.252061	1.000000	0.467236	0.720648
logMedInc	-0.093381	-0.857862	0.985048	0.704889	0.467236	1.000000	0.550274
logLf_size	0.423217	-0.360101	0.557318	0.313625	0.720648	0.550274	1.000000

7 Testable Hypotheses and Model Description

Using simple linear regression, I predict that poverty rate and the number of Dollar General stores will be positively related. Areas with higher poverty rates tend to also be areas that lack access to clean water and nutritious foods, which is the perfect breeding grounds for a new Dollar General. Recall that the corporation seeks position its stores in locations which generate trip-frequency by being an alternative to large-box grocery retailers. Furthermore, I hypothesize that higher incomes and labor force participation rates lead to less Dollar General stores. As incomes rise, people tend to purchase higher quality foods and household goods. Items from Dollar General are almost inferior goods, where demand for such goods drop as incomes increase. A county with a robust workforce and lowering unemployment will inevitably shift its purchasing habits towards consuming more normal and luxury goods. I also predict that areas with smaller labor forces, but not too small as to not have feasible sales revenues, will have more Dollar Generals than areas with very large labor forces. Counties with large amount of workers have a greater number of jobs available. This in turn leads to higher incomes on average, which makes Dollar General a less desirable option for food.

Table 4: Description of Model Variables

Variable	Description
dgCount	Number of Dollar General stores
povPcnt	Percentage of county population in poverty, $0 \leq povPcnt \leq 1$
lfpr	Labor force participation rate, ratio of employed in the labor force, $0 \leq lfpr \leq 1$
logMedInc	Natural log of real median income in 2018 dollars
logLF	Natural log of size of labor force

8 Model Output

Proceeding with log of median income and log of labor force, the initial regression model shown in Table 5 produced a surprising 0.353 R-squared value. This indicates that the economic variables used give some explanatory value to the amount of Dollar Generals in a location. However, *logMedInc* and *logLF* are the only variables statistically different from zero. The OLS Regression output states that there is evidence of multicollinearity between two variables, which confirms previous suspicions between poverty rates and incomes.

Table 5: Model 1 OLS Regression Results

Dep. Variable:	dgCount	**R-squared:**	0.353
Model:	OLS	**Adj. R-squared:**	0.327
Method:	Least Squares	**F-statistic:**	13.88
No. Observations:	133	**Log-Likelihood:**	-206.10
Df Residuals:	128	**Prob (F-statistic):**	4.48e-09
Df Model:	4		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	11.0584	32.270	0.343	0.733	-52.949	75.066
povPcnt	-5.5977	5.693	-0.983	0.328	-16.890	5.695
lfpr	35.1762	32.829	1.071	0.286	-29.941	100.293
logMedInc	-4.9693	1.251	-3.974	0.000	-7.450	-2.489
logLF	1.3038	0.179	7.297	0.000	0.949	1.658

Omnibus:	51.903	**Durbin-Watson:**	0.872
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	203.621
Skew:	1.621	**Prob(JB):**	6.09e-45
Kurtosis:	8.930	**Cond. No.**	4.02e+03

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

[2] The condition number is large, 4.02e+03. This might indicate that there are strong multicollinearity or other numerical problems.

An adjusted model using only *logMedInc* and *logLF* as independent variables produced a similar R-squared value, 0.332, which suggests that the change in median incomes and the size of the labor force can partially explain the number of Dollar Generals in a county. The output from Table 6 gives the estimated equation:

$$dgCount = 25.618 - 3.201 log(realMedInc) + 1.230 log(lf\_size)$$

The coefficient for *logMedInc* is negative, conveying that as median incomes rise, the number of Dollar Generals lessens. More specifically, for each percentage increase in real median income, the number of stores lessens by .0320 units. Similarly, for every percentage increase of the labor force size, the number of Dollar General stores increases by .0123 units.

Table 6: Model 2 OLS Regression Results

Dep. Variable:	dgCount	**R-squared:**	0.332
Model:	OLS	**Adj. R-squared:**	0.319
Method:	Least Squares	**F-statistic:**	25.82
No. Observations:	133	**Log-Likelihood:**	-207.78
Df Residuals:	130	**Prob (F-statistic):**	7.86e-10
Df Model:	2		

	coef	**std err**	**t**	**P> |t|**	**[0.025**	**0.975]**
Intercept	25.6148	6.390	4.008	0.000	12.943	38.287
logMedInc	-3.2005	0.657	-4.875	0.000	-4.502	-1.899
logLF	1.2299	0.173	7.091	0.000	0.886	1.574

Omnibus:	50.330	**Durbin-Watson:**	0.831
Prob(Omnibus):	0.000	**Jarque-Bera (JB):**	188.466
Skew:	1.584	**Prob(JB):**	1.19e-41
Kurtosis:	8.678	**Cond. No.**	567.

[1] Standard Errors assume that the covariance matrix of the errors is correctly specified.

9 Interpretation of Results

The model reveals a negative relationship between incomes and the number of Dollar General stores, which was predicted. This strengthens the argument that goods from Dollar General can be viewed as inferior goods. While further analysis is required to make definitive claims, this relationship is also suggestive that Dollar General's target market tends to be households on the lower end of the income scale. The model also shows that the relationship between the size of the labor force and Dollar General store count is positive, which contradicts the original hypothesis of these two variables being inversely related. One explanation could be that as a county grows economically, it invites more business to the region, Dollar General being no exception.

10 Conclusion and Discussion

It is unfortunate that this model is too simple to give a certain explanation on whether or not declining economic factors predict the number of Dollar Generals in an area. Other factors should be considered in a future analysis, such as educational attainment, race, and crime rates. A limitation that I had when creating this model was working with time-series data. While it was not too difficult to find, clean, and create a time series data frame, my mathematical rigor proved to be insufficient for properly modeling with time-series panel data.

Another suggestion for future research would be to work with geo-spacial data. The original web-scraped Dollar General location data includes coordinates for each store. It would be interesting to observe race, income, and large-box grocery store changes over time on a map, especially because different areas in a county may have different socio-economic structure. This can also help identify if Dollar General contributes to the creation of food deserts.

The goal of this analysis was to provide insight into the proliferation of Dollar General stores in Virginia. While this study did not produce solid evidence that under-served communities are the target market for the corporation, it did scratch the surface of what's possible to uncover about a corporation's goals with publicly available data. This analysis hints that economic decline in areas where there are a high number of Dollar Generals could be by design.

11 Appendix

References

[1] Dollar General Corporation. (2019). 2019 Annual Report and 2020 Proxy Statement. Retrieved from https://investor.dollargeneral.com/download/companies/dollargeneral/Annual%20Reports/AR_2019_Dollar%20General_Web%20PDF.pdf.

[2] Institute for Local Self-Reliance. (2018). The Impact of Dollar Stores and How Communities Can Fight Back [Fact Sheet]. Retrieved from https://cdn.ilsr.org/wp-content/uploads/2018/12/Dollar_Store_Fact_Sheet.pdf

[3] Dollar General. (n.d.). Store Locations and Map. Retrieved from http://www2.dollargeneral.com/About-Us/pages/storelocator.aspx

[4] U.S. Census Bureau. (2010). American National Standard Institute's 2010 Voting District Codes [Data file]. Retrieved from https://www2.census.gov/geo/docs/reference/codes/files/st51_va_vtd.txt

[5] U.S. Census Bureau. (2019). 2019 State, County, Minor Civil Division, and Incorporated Place FIPS Codes [Data file]. Retrieved from https://www.census.gov/geographies/reference-files/2019/demo/popest/2019-fips.html

[6] U.S. Census Bureau. (2018). 1999-2018 State and County Estimates, Small Area Income and Poverty Estimates [Data file]. Retrieved from https://www.census.gov/programs-surveys/saipe/data/datasets.html

[7] Bureau of Labor Statistics. (2019). Consumer Price Index for all Urban Consumers Research Series (CPI-U-RS) for all items, not seasonally adjusted, for 1978 through 2019 [Data file]. Retrieved from https://www.bls.gov/cpi/research-series/r-cpi-u-rs-allitems.pdf

[8] U.S. Census Bureau. (2014). American Community Survey 2014 Table and Geography Changes. Retrieved from https://www.census.gov/programs-surveys/acs/technical-documentation/table-and-geography-changes/2014.html

Code Preview

```python
import pandas as pd
import bls

BLSid = '<enter code here>'

df_emp = pd.DataFrame(bls.get_series(laus['emp'][0], 1999, 2018, BLSid).reset_index())
    .rename(columns={str(laus['emp'][0]): str(laus['name'][0] + '_emp')})
df_cnt = pd.DataFrame(bls.get_series(laus['lf'][0], 1999, 2018, BLSid).reset_index())
    .rename(columns={str(laus['lf'][0]): str(laus['name'][0] + '_lf')})
main_df = pd.merge(df_emp, df_cnt, on = 'date')

# Very proud of this code below
i = 0
for i in range(len(laus)):
    df_emp = pd.DataFrame(bls.get_series(laus['emp'][i], 1999, 2018, BLSid).reset_index())
        .rename(columns= {str(laus['emp'][i]): laus.iloc[i][0]+'_emp'})
    df_lf = pd.DataFrame(bls.get_series(laus['lf'][i], 1999, 2018, BLSid).reset_index())
        .rename(columns= {str(laus['lf'][i]): str(laus.iloc[i]['name']+'_lf')})
    merged_df = pd.merge(df_emp, df_lf, on = 'date')
    merged_df[str(laus['name'][i])] = merged_df[str(laus.iloc[i][0]+'_emp')] / merged_df[str(laus.iloc[i][0]+'_lf')]
    main_df = pd.merge(main_df, merged_df, on = 'date')

# Grouping DF by year
main_df['date'] =pd.to_datetime(main_df['date'], format = '%Y-%m')
main_df['year'] =pd.DatetimeIndex(main_df['date']).year
grouped_lfpr = main_df.groupby(['year']).mean().reset_index()
grouped_lfpr = grouped_lfpr.drop(['Unnamed: 0'], axis = 1)

# Creating labor force participation after every 2 columns
partRate = grouped_lfpr[grouped_lfpr.columns[::3]]
year = grouped_lfpr[['year']]
laborForce = grouped_lfpr.iloc[:, 2::3]
laborForce = (pd.merge(year, laborForce,left_index=True, right_index=True)).round(0)

# Melting in order to merge
melted_lfpr = pd.melt(partRate, id_vars = ['year'], var_name= ['county'], value_name='lfpr')
melted_lfpr = melted_lfpr.sort_values(by=['year'])

melted_laborforce = pd.melt(laborForce, id_vars= ['year'], var_name= ['county'], value_name= 'lf_size')
melted_laborforce = melted_laborforce.sort_values(by =['year'])
melted_laborforce['county'] = melted_laborforce['county'].str.replace('_lf', '')

completeDF = pd.merge(completeDF, melted_laborforce, how='left', on=['year', 'county'])
```

2018_df

	county	dgCount	povPcnt	realMedInc	lfpr	lf_size	logMedInc	logLF
0	Richmond city	13.0	0.223	48747.0	0.9640967792649190	117557.0	10.794398936070900	11.674678601323300
1	Bedford County	11.0	0.104	61186.0	0.9689718816570990	38270.0	11.021673684161300	10.552421578419700
2	Henry County	7.0	0.2	36471.0	0.9623441103077120	23672.0	10.504272703223900	10.072048194080000
3	Norfolk city	7.0	0.197	48519.0	0.963055229113188	111338.0	10.789710752787900	11.620325898579900
4	Virginia Beach city	6.0	0.075	76520.0	0.97083406207441	232337.0	11.24530742355420	12.355944182872500
5	Franklin County	6.0	0.153	53522.0	0.9687204534465600	26182.0	10.88784806331170	10.172827430740000
6	Suffolk city	5.0	0.109	69753.0	0.9672328663517600	44502.0	11.152715709511400	10.703289410964600
7	Pittsylvania County	5.0	0.164	44710.0	0.964024863038134	30488.0	10.707952469228000	10.325088442553700
8	Halifax County	5.0	0.145	43096.0	0.9584243932203020	15154.0	10.67118546436040	9.626019802491320
9	Scott County	5.0	0.185	40161.0	0.9669176714269350	9100.0	10.600651654454000	9.116029692504940
10	Tazewell County	5.0	0.182	42074.0	0.9552765805631910	15911.0	10.647185251694000	9.674765972907860
11	Chesapeake city	5.0	0.085	78846.0	0.9692122054071100	122298.0	11.275251861871700	11.714215968311800
12	Washington County	5.0	0.152	45510.0	0.9656757914687780	26663.0	10.725687361010700	10.191032115533900
13	Smyth County	5.0	0.204	40972.0	0.9596074786040740	13661.0	10.620644185556400	9.522300336887490
14	Danville city	5.0	0.256	36015.0	0.9485865679190630	19576.0	10.491690797323500	9.882059605122510
15	Lee County	5.0	0.248	34796.0	0.9583015778106380	8308.0	10.457257716627400	9.024974184996000
16	Portsmouth city	5.0	0.192	47343.0	0.958525807536726	44163.0	10.765174252416200	10.695642613426100
17	Louisa County	4.0	0.113	63714.0	0.9717367027607700	19758.0	11.0621595976319	9.89131375160442
18	Fredericksburg city	4.0	0.145	58448.0	0.964744220103675	13964.0	10.975892749035100	9.544237868224930
19	Henrico County	4.0	0.09	68581.0	0.9695373115297290	180763.0	11.135770807421200	12.10494205997970
20	Isle of Wight County	4.0	0.092	72993.0	0.9699048588999830	19348.0	11.19811882512180	9.870344333942870
21	Montgomery County	4.0	0.241	52538.0	0.970061300792312	49859.0	10.869291996279700	10.816954300719200
22	Rockingham County	4.0	0.087	61375.0	0.9728952787888300	41081.0	11.024757865096800	10.623301006492100
23	Roanoke city	4.0	0.202	42715.0	0.9671448645680800	48878.0	10.66230542558570	10.797082676478100
24	Mecklenburg County	4.0	0.187	44832.0	0.9587713667517630	12668.0	10.710677449136700	9.44683440765853
25	Augusta County	4.0	0.09	60556.0	0.9724428530646600	36796.0	11.011323835731800	10.513144422597000
26	Botetourt County	4.0	0.074	71874.0	0.9727210979380190	17282.0	11.182669864959400	9.757420776401350
27	Bristol city	4.0	0.205	36903.0	0.9617721300778630	7178.0	10.516048127536900	8.878776071707550
28	Charlotte County	4.0	0.193	41382.0	0.9627822103060500	5209.0	10.630601282659300	8.558143177745190
29	Page County	3.0	0.139	49073.0	0.9575432896431780	11893.0	10.801064264366200	9.383705270727250
30	Nelson County	3.0	0.123	56690.0	0.9684864618506880	7318.0	10.945353107318300	8.898092345579150
31	Newport News city	3.0	0.152	50283.0	0.9630940866521280	88574.0	10.825422326795400	11.391593639802600
32	Westmoreland County	3.0	0.164	51414.0	0.9627533547858290	9371.0	10.847665787897200	9.145375093123820
33	Orange County	3.0	0.094	63681.0	0.9693465520832170	17013.0	11.061641523912600	9.741733036682140
34	Hanover County	3.0	0.052	91028.0	0.9734712844120810	58777.0	11.418922430479100	10.981505900902500
35	Hampton city	3.0	0.154	54763.0	0.9588653382003620	64262.0	10.910770062416000	11.070723755746100
36	Dinwiddie County	3.0	0.125	57257.0	0.9644513080669850	13550.0	10.955305184684400	9.514141826307850
37	Giles County	3.0	0.124	50591.0	0.9659829875867960	7836.0	10.831528973842900	8.966483779064430
38	Campbell County	3.0	0.113	51525.0	0.965699297911228	25890.0	10.84982240575870	10.161612072745600
39	Prince George County	3.0	0.089	68133.0	0.9631252820214260	14986.0	11.129216956263700	9.614871710924260
40	Chesterfield County	3.0	0.076	80734.0	0.9702686837710230	186120.0	11.29891507903720	12.134146905958600
41	Shenandoah County	3.0	0.104	55283.0	0.9710720311624660	22169.0	10.92022072614410	10.006450195594000
42	Patrick County	2.0	0.155	42862.0	0.9608209162189640	7435.0	10.665740931494600	8.913953858894260

completeDF

	year	county	dgCount	povPcnt	realMedInc	lfpr	lf_size
0	1999	Accomack County	0.0	16.1	42200.44	0.93595074436044	14765.0
1	2000	Accomack County	0.0	17.1	43587.85	0.9698260121726640	18126.0
2	2001	Accomack County	0.0	16.3	41107.37	0.965979177165454	18347.0
3	2002	Accomack County	0.0	17.7	40451.25	0.9579839526810440	19016.0
4	2003	Accomack County	0.0	15.6	41144.7	0.9559716660312220	19225.0
5	2004	Accomack County	0.0	14.9	41652.14	0.9525315388503660	19062.0
6	2005	Accomack County	0.0	18.3	42325.28	0.9527676291918390	18785.0
7	2006	Accomack County	0.0	15.4	46487.18	0.9570205677361820	18569.0
8	2007	Accomack County	0.0	16.8	44453.7	0.9587765275654850	18779.0
9	2008	Accomack County	0.0	20.6	43917.7	0.9499656145812180	18990.0
10	2009	Accomack County	0.0	18.3	42836.73	0.9349491548074170	19704.0
11	2010	Accomack County	0.0	20.5	43064.85	0.9208569656468530	16804.0
12	2011	Accomack County	0.0	19.3	42198.6	0.9159762149794720	16590.0
13	2012	Accomack County	0.0	19.9	40493.92	0.9211782006651400	16418.0
14	2013	Accomack County	0.0	19.3	41098.01	0.92774142320689	16229.0
15	2014	Accomack County	1.0	19.4	40759.75	0.9329170658043270	16051.0
16	2015	Accomack County	0.0	20.4	41007.63	0.9452638647164720	15877.0
17	2016	Accomack County	0.0	20.0	40851.7	0.9504632156268390	15783.0
18	2017	Accomack County	0.0	17.8	45111.5	0.9546081015490880	16628.0
19	2018	Accomack County	1.0	17.3	42879.0	0.9611500659727400	16747.0
20	1999	Alexandria city	0.0	7.9	82388.6	0.9778021765017550	74455.0
21	2000	Alexandria city	0.0	7.5	84254.16	0.982082298987378	80943.0
22	2001	Alexandria city	0.0	7.2	82944.11	0.9728752721219060	81630.0
23	2002	Alexandria city	0.0	7.8	82824.28	0.9655514044568280	83146.0
24	2003	Alexandria city	0.0	8.8	81219.14	0.9699762012537400	82495.0
25	2004	Alexandria city	0.0	8.3	80909.57	0.9724608996053680	83784.0
26	2005	Alexandria city	0.0	7.7	83458.28	0.9738907495981410	84746.0
27	2006	Alexandria city	0.0	7.2	97793.5	0.9776398252237680	86832.0
28	2007	Alexandria city	0.0	8.3	95627.17	0.9777355715476850	89476.0