# Assessing the Impact of Neighborhood Change to NYC's FRESH Program

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### What is the FRESH program?

FRESH promotes neighborhood grocery store development through **zoning** and tax incentives, in areas zoned for FRESH through the Supermarket Needs Index.

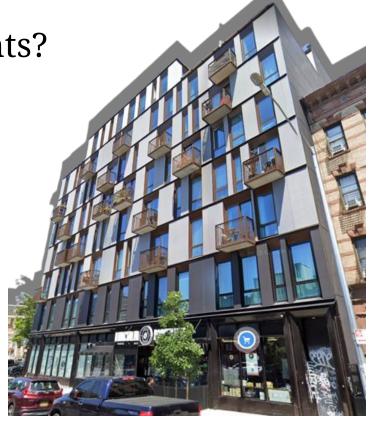


How does this affect residents?

Over 50 stores have been approved under the FRESH program...

\$140M invested in NYC's economy...

...but the power is in the developer's hands.

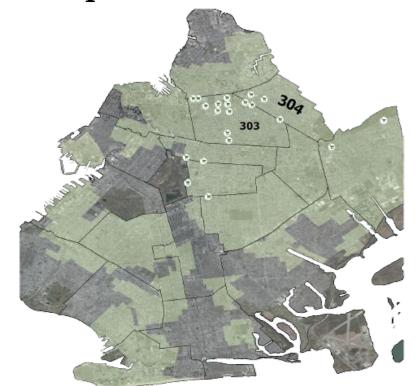


Source: 633 Marcy Ave, Google Street View (July 2022)

# How could this program be improved?

Ensure a more equitable distribution of FRESH developments through deeper quantitative analysis of the implementation results from the last decade. (my thesis!)

DCP needs to assess additional indicators that may be a factor to FRESH store clustering.



### Research Questions

1. Are FRESH developments in Brooklyn significantly clustered?

2. In Brooklyn and Bedford-Stuyvesant:

What is the **impact of a neighborhood change indicator** to the likelihood of **creating a fresh zone** within a census tract?

What is the impact of a neighborhood change indicator to the likelihood of **creating a fresh store** within a census tract?

# Data Sources

#### NYC Open Data

FRESH zones [poly]

BYTES of the BIG APPLE<sup>TM</sup> - Archive (2019)

FRESH food stores [point]

DCP Open Data email request

Borough Boundaries [poly]

Community Districts [poly]

#### U.S Census Bureau

via Tidycensus:

2011-2019

Total Population

Race (white alone)

Median Household Income

Year Structure Built

# **Transform Data**

#### Census Data

Change in household income, 2011-2019

Adjusted to 2019 inflation rates (where CPI 2019 / CPI 2011 = 1.143)

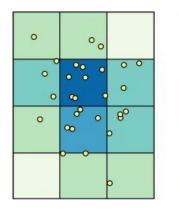
Change in white population, 2011-2019

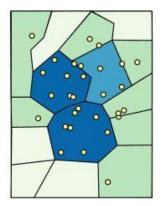
Created % with total population rates (2011,2019)

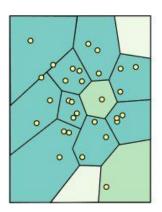
#### Census Data

Year Structure Built (where 'new buildings' are 2014 or later, 2019 only)

Normalize density to represent # of new buildings / square mile



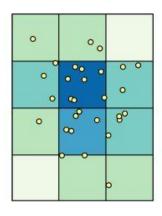


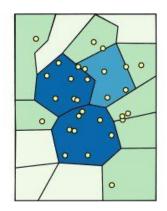


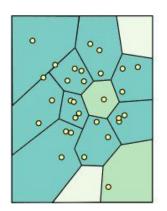
#### **FRESH stores**

Fresh Food Stores by census tract

Normalize density to represent # of FRESH stores / square mile







#### FRESH Binary Categories

Define census tracts that have a FRESH store

calculated number of stores through a value\_count of GEOID (unique ID)

created binary category column where all tracts with at least one store were labeled '1'

### FRESH Binary Categories

Define census tracts that are in a FRESH zone

clipped fresh zone to brooklyn boundary

joined census tracts that are only within the fresh zone, created a field to mark these tracts as "1"

joined to full dataset, filled NAs to create 0/1 categories

# Modeling

# Part I: Moran's I on FRESH Food Stores

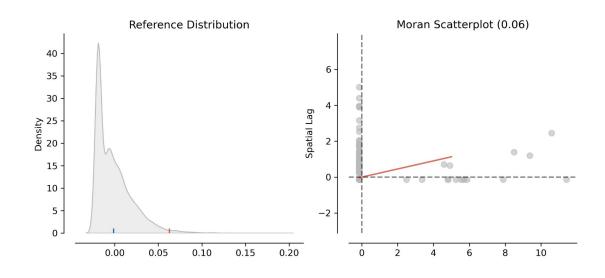
On Queen Contiguity

#### Global Moran

On normalized density of FRESH food stores in Brooklyn:

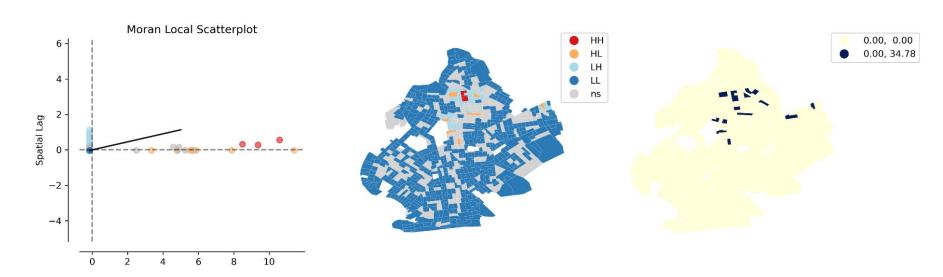
moran.I = 0.0627

p-value = **0.0**13

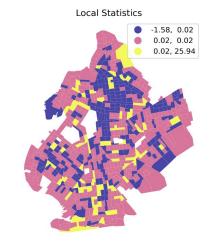


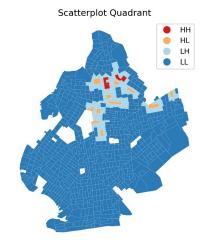
#### Local Moran

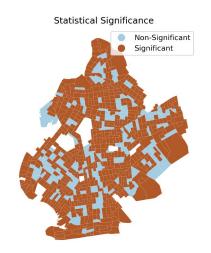
On normalized density of FRESH food stores in Brooklyn:

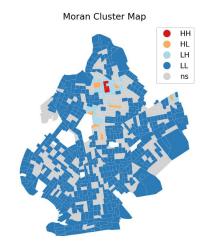


#### Local Moran









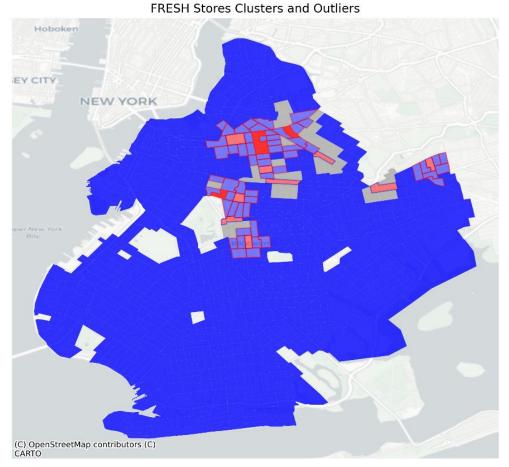
#### Local Moran

**HOT SPOTS** 

**COLD SPOTS** 

**DIAMONDS** 

**DOUGHNUTS** 



# Part II: Logistic Regression

Through sensitivity analyses

#### Models

- 1. FRESH zone Brooklyn
- 2. FRESH store Brooklyn
- 3. FRESH store Bedford-Stuyvesant

# Understanding the results

Logistic Regressions are NOT linear

Easier to interpret results in piecemeal fashion

To do this, test changes in neighborhood indicators with one census tract

2 census rows, with different characteristic breakdowns, are selected as test variables

# "Gentrified Test Variable": Census Tract 129.01





# "Not Gentrified" Test Variable: Census Tract 374.02





INFU-615

Source: NYCDCP Population Fact Finder

# Model 1: Fresh Zones in Brooklyn

Predicting the likelihood of a census tract being considered in a fresh zone

	Lo	ogit Regres:	sion Res	ults			
Dep. Vari	iable:	fresh_zor	ne <b>No.</b>	Observ	ations:	745	
M	odel:	Logit		Df Res	iduals:	741	
Me	thod:	MLE		Df Model:		3	
Date: Wed,		03 May 2023 P		Pseudo R-squ.:		0.05380	
Time:		12:44:4	12:44:49 <b>Lo</b>		ihood:	-461.04	
converged:		True		LL-Null:		-487.25	
Covariance Type:		nonrobust		LLR p-value:		2.425e-11	
	coef	std err	z	P> z	[0.02	5 0.975	
Intercept	-0.2528	0.091	-2.783	0.005	-0,43	1 -0.07	
inc_change	-3.304e-05	5.31e-06	-6.226	0.000	-4.34e-0	5 -2.26e-0	
yt_change	2.2769	0.758	3.003	0.003	0.79	3.76	
new built	-4.265e-05	0.000	-0.335	0.738	-0.00	0.00	

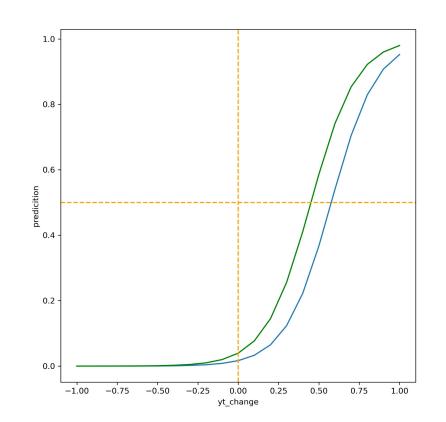
to the production provides

## Model 1 Testing: Change in % of White Population

# GENTRIFIED test variable

# NON-GENTRIFIED test variable

Stronger predictions of a fresh zone based on white population changes are seen in the gentrified test variable.

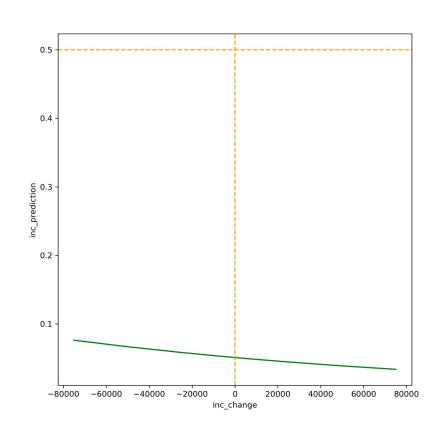


## Model 1 Testing: Change in Household Income

# GENTRIFIED test variable

# NON-GENTRIFIED test variable (SAME)

Both variables decrease their predictions by the same rate as household income increases.

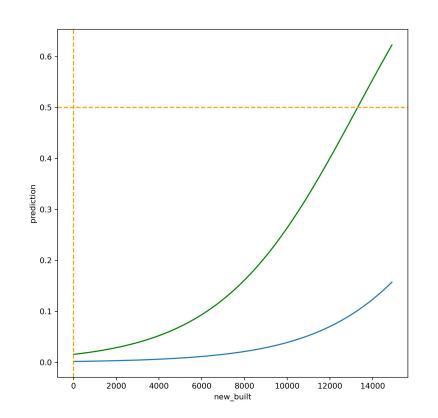


# Model 1 Testing: Change in New Buildings

# GENTRIFIED test variable

# NON-GENTRIFIED test variable

Stronger predictions of a fresh zone based on # of new buildings per square mile are seen in the gentrified test variable.



# Model 2: Fresh Stores in Brooklyn

Predicting the likelihood of a census tract being considered for a fresh store development within Brooklyn

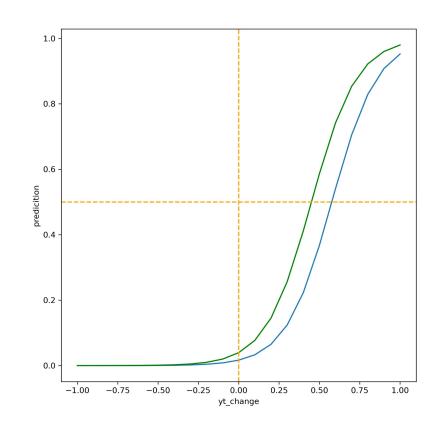
	L	ogit Regres	sion Resu	lts				
Dep. Variable:		fresh_store No		No. Observations:			745	
M	Model:		git	Df Residuals:			741	
Me	Method:		MLE		Df Model:		3	
Date: Tue,		02 May 2023 <b>P</b>		seudo R-squ.:		0.07832		
Time:		16:50:	15 <b>Log-Likeli</b> l		hood:	100d: -7		
converged:		True		LL-Null:		-7	7.280	
Covariance Type:		nonrobu	ıst	LLR p-value:		0.007031		
	coef	std err	z	P> z	[0.	025	0.9	75]
Intercept	-4.1012	0.337	-12.183	0.000	-4.	761	-3.4	441
inc_change	-5.72e-06	1.48e-05	-0.386	0.699	-3.486	-05	2.33e	-05
yt_change	7.0766	2.308	3.067	0.002	2.	554	11.6	500
new_built	0.0003	0.000	1.949	0.051	-1.81e	-06	0.0	001

# Model 2 Testing: Change in % of White Population

# GENTRIFIED test variable

# NON-GENTRIFIED test variable

Stronger predictions of a fresh zone based on white population changes are seen in the gentrified test variable.

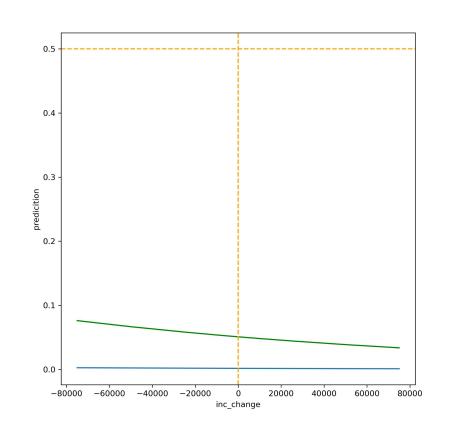


## Model 2 Testing: Change in Household Income

#### **GENTRIFIED test variable**

# NON-GENTRIFIED test variable

Stronger predictions of a fresh zone based on household income changes are seen in the gentrified test variable.

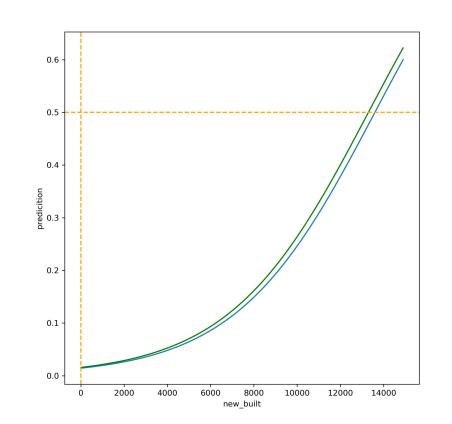


## Model 2 Testing: Change in New Buildings

# GENTRIFIED test variable

# NON-GENTRIFIED test variable

Both variables increase their predictions by the similar rate number of new building per square mile increases.



# Model 3: Fresh Stores in Bedford-Stuyvesant

Predicting the likelihood of a census tract being considered for a fresh store development within Bedford-Stuyvesant

	Log	git Regressio	n Resul	ts					
Dep. Vari	able:	fresh_zone	No.	. Observations:			66		
М	odel:	Logit	t )	Df Resi			62		
Met	thod:	MLE		Df N		lodel:		3	
	Date: Tue, 0	2 May 2023	Pseudo R		-squ.:	0.03	3066		
1	Гіте:	16:48:45	Lo	g-Likeli	hood:	-41	.936		
converged:		True		LL-Null:		-43.262			
Covariance Type:		nonrobust		LLR p-value:		0.4483			
	coef	std err	z	P> z	[0.	025	0.97	5]	
Intercept	1.0648	0.491	2.167	0.030	0,	102	2.0	28	
inc_change	-2.996e-05	2.08e-05	-1.442	0.149	-7.07e	-05	1.08e-	05	
yt_change	-0.7537	2.625	-0.287	0.774	-5.	899	4.3	92	

0.000

Logit Pagrossian Pagulta

FAIL (see p values)

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new built

3.796e-07

-0.001

0.999

0.001

# Ecological Fallacy

"inferences about the nature of specific individuals are based solely upon aggregate statistics collected for the group to which those individuals belong"

Source: wiki.GIS

# Lessons Learned

#### Takeaways

- Logistic regression results can be difficult to interpret
  - Cannot present in a linear fashion, results may be misleading
- As the spatial extent narrows, the significance of statistical outputs quickly diminish. City and Borough-wide extents are preferred moving forward.

#### Next Steps

- Address more indicators
  different race breakdowns
  other indicators quantifying poverty and hunger
- Conduct more web research before selecting test variables chosen primarily on census numbers, lacks local context

# Thank You!

Follow-Up Questions:

- What other neighborhood indicators should I consider?
  - General notes / feedback on design?