Local Retail Prices, Product Variety and Neighborhood Change

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Abstract

We study how local grocery markets within a city are affected by changes in housing markets. Our empirical strategy exploits a shift in the spatial distribution of construction activity induced by a large-scale, place-based tax exemption in the city of Montevideo. The introduction of new housing stock induced by the policy causes a reduction in grocery prices of 2.3%, and an increase in locally available product varieties. Using insights from a multi-product model of imperfect competition and estimates for different types of stores, we show these changes are the result of incumbents' response to an increase in local demand.

Keywords: Retail Prices, Housing Stock, Neighborhood Change.
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1. Introduction

The availability of grocery stores and supermarkets is not homogeneous within cities. Differences in the local consumer base across locations can shape the availability of these stores as well as the prices and varieties of the goods they sell. Therefore, physical changes in neighborhoods that influence this consumer base can affect local retail options. The direction of these changes – as well as their welfare and distributional consequences – will in general depend on the local supply response, both in terms of changes in the varieties of goods sold and in the entry of new grocery stores.

In this paper, we study how neighborhood change affects local retail opportunities within cities. Specifically, we test whether large scale development of new housing stock within a city influences the price and variety of groceries available locally, as well as the density of stores in affected neighborhoods. This is motivated by the notion that residential development can affect incumbent households through indirect channels – i.e., beyond direct effects on the market for housing services – that are relevant to the debate around the welfare impacts of neighborhood change. The focus on groceries in particular is motivated by the fact that these goods have a large consumer base and represent a larger share of spending for households with relatively lower incomes.

New development can affect the market for groceries because it increases local demand for these goods. In the first place, changes in housing stock may increase residential density – i.e., the volume of consumers at each location – thus scaling up demand. In the second, new stock can affect neighborhood composition. Previous studies have shown that the age of the housing stock can partly explain the dynamic of neighborhoods' economic status (Rosenthal, 2008; Brueckner and Rosenthal, 2009; Rosenthal, 2020). Newly built units often attract affluent residents with a high willingness to pay for this type of housing (Brueckner, 2011). Through both channels, the local demand for goods and the demand for different varieties may increase with new housing development.

Estimating how residential development affects local conditions in the market for groceries requires dealing with a reverse causality problem: residential development is shaped by local demand for housing and is therefore influenced by local retail options. In addition, neighborhood characteristics such as accessibility to jobs or local crime rates can affect housing demand and grocery supply conditions. To overcome these problems, we exploit quasi-experimental variation from a major housing policy intervention that induced a large re-location in the development of new stock within the city of Montevideo, Uruguay. The policy provides tax benefits to developers building housing in a pre-defined middle-income area of the city, effectively subsidizing development in those locations. Developers used the program intensely, with total investment through this scheme standing at a remarkable 1.5% of the GDP in the first five years of the policy. New units sold were typically high-quality flats in multi-family buildings marketed to mid-high/high-income households. We view this policy as a shock to the spatial distribution of residential construction inducing exogenous variation in new housing around existing stores and supermarkets.[1] Our empirical strategy is based on event-study specifications that compare locations in the city affected by the policy shock with nearby unaffected locations.

Our analysis is carried out using a detailed product-level database of daily posted prices compiled by the General Directorate of Commerce (DGC, by its Spanish acronym), a branch of the Ministry of Economy and Finance in Uruguay. The data comprises detailed information from grocery stores all over the country, including hundreds of stores in Montevideo. An advantage of this database relative to the scanner data popular in most studies of retail markets and prices in developed countries is coverage: because the retail landscape in Montevideo includes a series of medium and small stores alongside larger supermarket chains, scanner data platforms have incomplete coverage in this context.

Using this database, we test whether neighborhood change induced by the policy influenced the price of groceries, the product variety, and the convenience in access to stores available locally to consumers. Regarding price levels, we find that stores in areas directly affected by the policy experience a reduction in grocery prices. Our reduced-form estimates point to an effect on prices between -2% and -2.6%. Thus, our findings indicate that neighborhood change induced by the introduction of new housing stock results in higher purchasing power for incumbent households in the vicinity of affected stores.

This change in price levels is accompanied by a substantial increase in available varieties in neighborhoods receiving the residential development shock. The fraction of available product varieties in affected stores increases by roughly 7 percentage points. In terms of convenience, we find a positive though imprecisely estimated effect of the policy on the density of grocery stores available in affected areas. We can confidently rule out reductions in store access that compensate for the increase in varieties and reduction in prices.

Taken together, our results indicate that the local increase in demand induced by the change in housing stock improves the retail landscape for households in these neighborhoods: the prices of groceries experience a moderate reduction, the varieties available increase substantially, and there is evidence of some improvement in the convenience of access to stores. In light of this evidence, public concerns about the negative effect of neighborhood change on equitable access to groceries may not be warranted.

Some of these results appear counter-intuitive. For example, local prices respond negatively to what we interpret as a positive demand shock. To rationalize this finding, we introduce a theoretical framework based on Mayer et al. (2014) in which multi-product firms competing in quantities face an increase in local demand. In our framework, this increase in demand can lead to an equilibrium with lower markups if it is accompanied either by an increase in entry or an increase in the varieties available to consumers.

We report evidence consistent with the second channel: incumbent stores were responsible for the reduction in prices and the increase in product variety associated with the policy. This result is consistent with findings in Jaravel (2019) where increasing relative demand

[1] For an analysis of the specific effects of the policy on housing markets, see work in González-Pampillón (2021).

for certain goods reduces prices and increases variety. Regarding the entry channel, we find no net entry of stores associated with the introduction of new housing stock. The modest levels of entry and exit that did take place cannot explain the improvement in retail conditions. Complementary evidence shows that our finding of improved retail conditions cannot be accounted for by alternative explanations such as the introduction of new commercial space in the ground floor of new buildings or differential changes in prices across the quality distribution of sold goods.

This article contributes to the growing literature on urban consumption that emerged following the seminal contribution in Glaeser et al. (2001). Part of this literature has focused on studying how locations differ in the prices and varieties of consumption goods and services available. Handbury and Weinstein (2015) and Handbury (2021) study differences between US cities in both the prices of goods and the varieties available to consumers across the income distribution. Schiff (2014) and Couture (2016) analyze differences in the variety of restaurants resulting from higher density in US cities. Our paper connects to this literature by looking at how neighborhood change affects differences in the price and variety of goods offered in the local market for groceries.

Our paper is also related to the growing literature on endogenous consumption amenities in cities (Diamond, 2016; Guerrieri et al., 2013; Almagro and Domınguez-Iino, 2019). Allcott et al. (2019) use a structural model of grocery demand to conclude that differences in the supply of groceries at the local level explain only a small fraction of nutritional inequality in the United States. Couture et al. (2019) use a quantitative spatial model to quantify the effect of changes in the income distribution on both sorting patterns and the endogenous quality of neighborhoods. Our study contributes to this literature by providing empirical evidence on how local supply conditions respond endogenously to local shifts in demand arising from neighborhood change.

Several studies in the neighborhood change literature have focused specifically on the revival and gentrification of downtown areas of cities in the United States. Glaeser et al. (2001) had shown a change in the pattern of sorting of high income households between downtowns and suburbs over two decades ago. Recent work in Couture and Handbury (2020) emphasizes the role of restaurant variety and quality, as well as other non-tradable services, in shaping the continued sorting of young college graduates into urban cores. Baum-Snow and Hartley (2020) also document the process of population growth and gentrification in downtown neighborhoods. They emphasize how differences in the valuation of amenities by racial groups as well as in the availability of suburban job opportunities shaped the process of urban revival. Our paper shows that local changes in demand can result in responses by local suppliers that generate endogenous change in the attractiveness of affected neighborhoods.

Naturally, this paper is also related to the broader literature on the effects of gentrification and neighborhood change on local outcomes. Previous work in this literature has analyzed residential mobility patterns in gentrifying neighborhoods attempting to measure the extent of displacement of original residents. A group of studies finds little evidence of higher out-migration of these residents (Vigdor, 2002; Freeman, 2005; McKinnish et al., 2010; Ellen and O'Regan, 2011a,b; Ding and Hwang, 2016). Three recent studies (Aron-Dine and Bunten, 2019; Waights, 2018; Brummet and Reed, 2019) find instead that gentrification indeed leads to out-migration and displacement. Brummet and Reed (2019) also show that original home-owners who stay after the neighborhood gentrifies benefit from higher house values and increased employment levels. Closer to our work here, Asquith et al. (2021) study the effect of new residential stock on local housing prices and rents, finding a depression of local rents despite the new stock being occupied by relatively high-income residents. Our contribution to this broad literature is to look specifically into how neighborhood change affects local retail options for households.[2]

Finally, this paper is also related to previous work on the relationship between housing and retail markets. Stroebel and Vavra (2019) estimate how changes in house prices affect local retail prices. They argue that their estimates are not driven by changes in demographic or gentrification patterns. Instead, they point to changes in the behavior of existing home-owner residents due to changes in their housing wealth – derived from changes in house prices – which lead local retailers to increase mark-ups. While we also look at interactions between these two markets, we instead study how a process of physical change in neighborhoods affects retail conditions in local stores.

2. Background

2.1. Institutional Setting

This section describes the place-based policy that underpins our strategy to study the effect of new housing stock on local grocery markets.

In August 2011, the Uruguayan government passed Law 18,795, entitled Ley de Acceso a la Vivienda de Interés Social (which roughly translates to Access to Housing of Social Interest Law, henceforth LVS for its Spanish Acronym).[3] The LVS aims at increasing the stock new build housing by means of a series of place-based tax benefits for the development of new residential units. Developers and private investors building new stock in certain locations are exempted from paying corporate tax (25% rate) on profits made on the sale of the new housing units, while house rents are partially exempted from personal income and corporate taxes for a period of 9 years.[4] Under the scheme, 540 new construction projects were promoted from December 2011 until December 2018, involving almost 17,000 new units. The total amount invested during this period rose to almost USD 1.4 billion, amounting to

[2]The link between retail access and neighborhood change has also been studied by the urban planning literature on *retail gentrification*. See for example, Mermet (2017), Zukin et al. (2009) and González and Waley (2013). These studies tend to focus on how the entry of boutique or gourmet shops replaces traditional retailers rather than on the effect of neighborhood change on the prices and varieties of grocery goods available locally. Despite this difference in focus, our finding that new development results in the entry of larger retailers is relevant for this line of work.

[3]The word *social* here is somewhat misleading. As discussed below, the vast majority of new units built under the aegis of the law were marketed to middle or middle-high income households.

[4]Other minor fiscal advantages include the exemption of the wealth tax over land and improvements during construction, as well as, over produced and subsequently rented units until nine years. They are also exempted to pay the transfer tax in case of buying unsold units. Finally, the law establishes tax credits for value-added tax on national and imported inputs.

roughly 1.5% Uruguayan GDP. The city of Montevideo concentrated 65% of the total projects (349 projects).[5]

The LVS policy can be used to subsidize projects of up to 100 new units by land lot. However, there are exceptions made for projects performed in large vacant lots or in parcels with abandoned housing or factories. Anecdotal evidence suggests many of the developments carried out through the policy indeed used parcels with vacant or derelict buildings. Eligibility conditions include unit size restrictions dependent on the number of bedrooms (i.e., between $32m^2$ and $50m^2$ for one bedroom units, increasing with each additional bedroom up to four).[6] LVS units also had to adhere to the guidelines laid down in the National Housing Plan and other regulations on quality. Compliance of LVS projects with these conditions was enforced via a vetting process involving the National Housing Agency (ANV) the Ministry of Economics and Finance and the Ministry of Housing. The resulting units created under the aegis of the scheme were usually high quality apartments in multi-family developments. Appendix Figure A.1 shows the distribution of quality for the LVS units and the existing stock in Montevideo. Around 95% of the LVS units were assessed as 'Excellent' by the Municipal Property Registry, while the average non-LVS dwelling for the city is assessed as having regular quality. The average time between the approval of a new project and the completion of building activities was of 21 months.

Eligibility for the subsidy for new construction offered by the LVS policy is place-based. The relevant regions in Montevideo are shown in Figure 1. The tax benefit only applies in the area labeled as S and shaded in dark gray in the map. This region represents 52% of the total urbanized area, and is composed of both central and peripheral neighborhoods. It is highly heterogeneous in income, with a coefficient of variation of 30% in per capita disposable household income. The unsubsidized area is shaded in light gray in Figure 1 comprises most of the high-income neighborhoods in the city, with an average real per capita income that doubles the one in the subsidized area. Appendix Figure A.4 shows that this pattern is also observed for housing prices.[7] Figure 1 displays the spatial distribution of the LVS projects.

The boundaries of the subsidized area were defined jointly by the Ministry of Housing, the Ministry of Economics and Finance, and the Local Government of Montevideo's City Council. While there are no official documents explaining how the delimitation of the LVS borders was established, the border follows along some of the city's main avenues.

In what follows, we will use the LVS as a source of exogenous variation in the location of new residential development in Montevideo. Figure 2 illustrates how the LVS policy shifted new construction activity in the city. Panel A shows a heatmap for LVS projects carried out between the onset of the policy and 2018. We can observe these are located in the eligible region and, in most cases, are concentrated close to the region's boundary. Panel B illustrates how the policy induced a change in *overall* construction activity near the this boundary. For

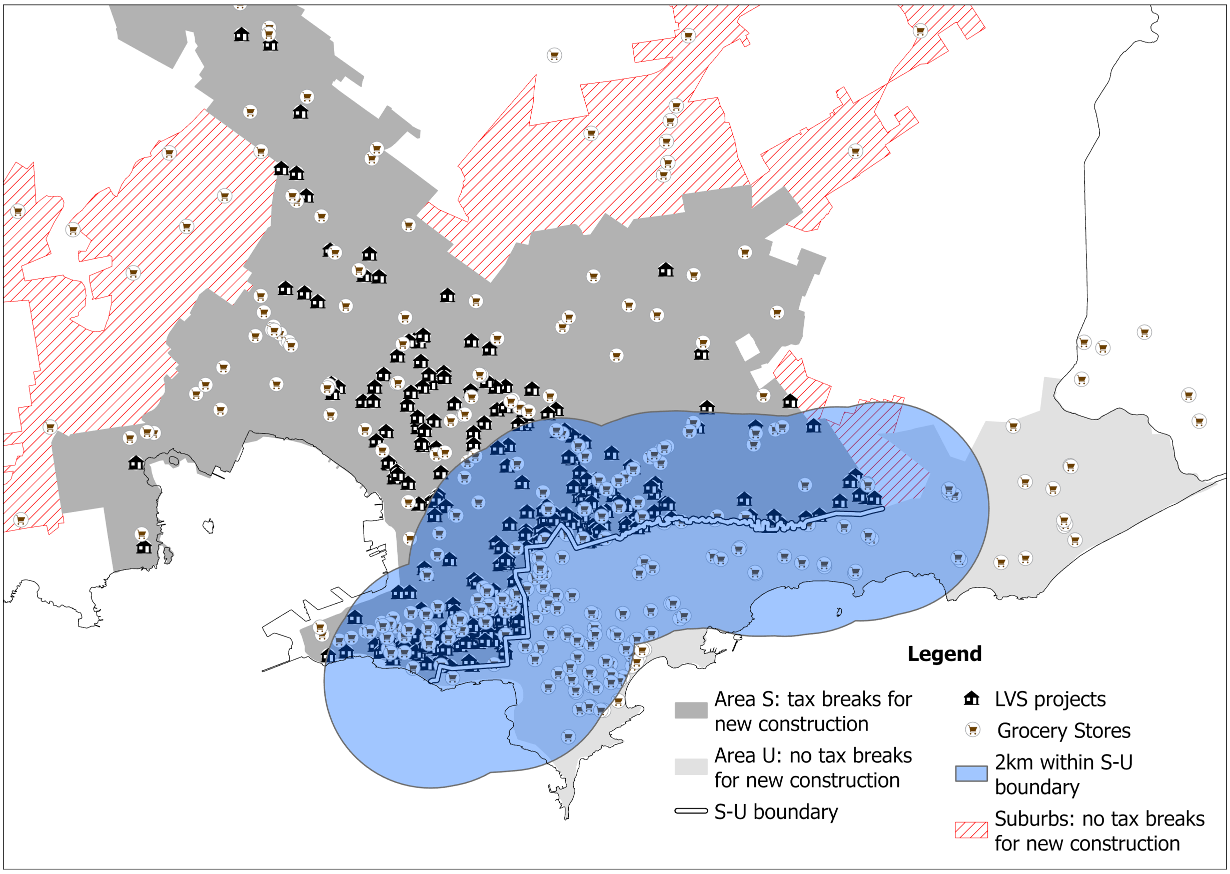
[5] Figure A.3 shows an example of a project performed in Montevideo before and after its implementation.

[6] Subsequent changes in regulation increased the lower bound of one-bedroom LVS units to $35m^2$.

[7] The unsubsidized area also has better quality housing stock on average (see Appendix Figures A.1 and A.2). Quality is measured by the local municipal register based on structural property characteristics.

FIGURE 1

PLACE-BASED SCHEME FOR NEW CONSTRUCTION PROJECTS IN MONTEVIDEO (URUGUAY)

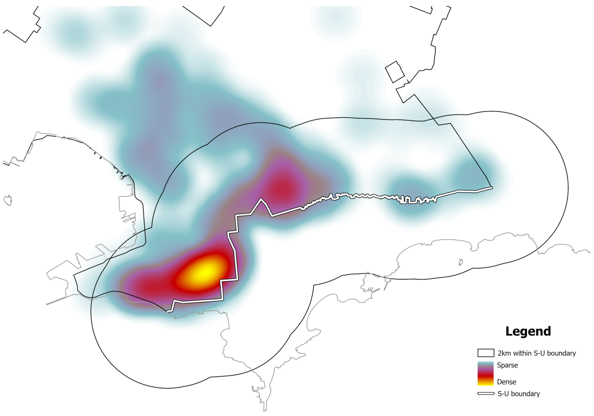


Notes: The policy was introduced in August of 2011. The subsidy for new construction projects only applies in the grey-area S. Development in area U received no exemptions. Black housing icons correspond to LVS projects approved for development in the period 2011-2019. Grocery icons correspond to the groceries included in our sample. The 2km buffer from the S-U border denotes our area of analysis. Development in the dashed area (referred as the suburbs) did not receive exemptions.

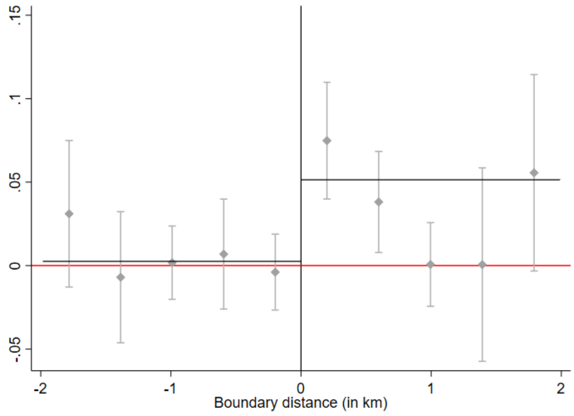
census tracts at different distance bands around the boundary, we calculate the average change in new residential area built between the pre-policy period (2004-2010) and the period in which LVS properties came on the market (2013-2019). We plot the change in the vertical axis against distance to the boundary, with positive distances corresponding to census tracts in the eligible region. We can observe that areas within the eligible region and close to the boundary experienced a significant increase in total new building activity in these periods. This is the spatial variation that we will use for identification.

It is also important to highlight the temporal structure of the shock to local housing supply induced by the policy. The LVS vetting process, the time required to obtain building permits from the city government, and the protracted build times usually associated to multi-family developments, meant it took several years before the first LVS properties came on the market. The timing of accumulated final sales of units in LVS developments approved between 2011 and 2014 are displayed in the Panel C of Figure 3. We can see that very few sales – less than 5% – had taken place before 2015, and roughly 60% of sales did not come until 2017. As a result, our empirical strategy will only provide suitable exogenous variation

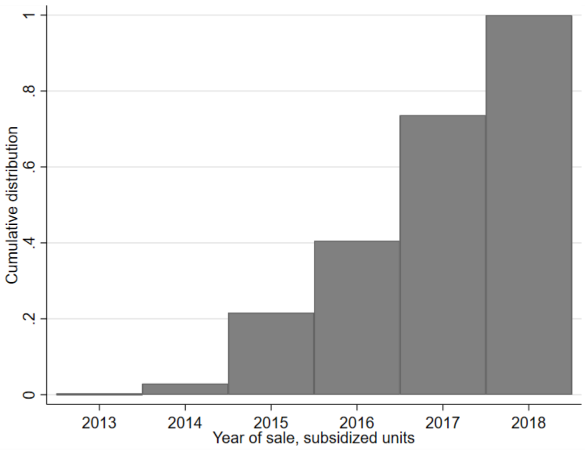
Figure 2
LVS and New Building Activity in Montevideo



(a) LVS Projects Heat Map



(b) Change in All New Building



(c) Timing of LVS Property Sales

Note: **Panel A** presents a heat-map of LVS projects in the city of Montevideo. Red and yellow tones denotes a higher concentration of LVS projects. As in Figure 1, the 2km buffer from the S-U border (the white solid line represents our area of analysis. The other solid black line corresponds to the boundary of the region eligible for LVS housing development. **Panel B** illustrates changes in construction activity between the 2004-2010 and the 2013-2019 periods, as measured using information from the municipal property registry. The horizontal axis represents distances to the LVS region boundary with negative distances corresponding to locations outside this region and positive distances to locations inside the regions. Black markers correspond to binned averages by distance. Vertical segments correspond to 95% CIs for those averages. Solid horizontal black lines correspond to averages calculated on each side of the boundary. **Panel C:** Timing of market sales of units from LVS projects that were approved for development between 2011 and 2014. Vertical axis represents frequencies relative to all sales up to 2018. Own calculations based on combining official data on LVS projects with data on housing transactions from the National Registry Office for the period 2011-2018.

in the stock of new properties in the final years of our sample, a factor we will take into account when using this variation to estimate the effect of neighborhood change on local retail conditions.

2.2. Geography of Grocery Shopping in Montevideo

Our empirical strategy exploits the effect of the LVS policy on the geography of new construction to study how neighborhood change affects the prices, varieties and ease of access of households to grocery shops. An implicit assumption in this analysis is that households access grocery stores locally. This means both that changes in a neighborhood affect the demand faced by its stores and that the retail landscape faced by households is shaped by the prices, varieties and stores available to them locally. Previous work has shown that consumer demand for groceries tends to be quite local. For example, structural estimates in Eizenberg et al. (2021) using Israeli data indicate a 1km change in distance to a neighborhood reduces retail demand from that neighborhood by 35%. Yet this study reports a substantial degree of cross-neighborhood shopping.

Survey evidence indicates households in Montevideo tend to make their grocery purchases locally. Results from the Montevideo Travel Survey for 2016 – outlined in Mauttone and Hernández (2017) – indicate that 75% of trips for the purchase of groceries are done on foot, and only 16% are done by car. The average duration of trips for purchasing groceries is only 12 minutes, representing around 1km walking distance using Google maps. A separate national survey on purchasing habits referenced by the Uruguayan Competition Commission indicates that only 12% of households in Uruguay report doing their regular shopping in locations that are more than 10 blocks (roughly 1km) away from their home.[8] According to the same source, location is the most frequently cited motive for choosing a specific store to buy groceries overall (61% of respondents). Together, these patterns in shopping practices mean that grocery markets are indeed local and that the scale of cross-neighborhood shopping is limited in our context.

The local nature of grocery shopping in Montevideo is, at least in part, shaped by the limited degree of car ownership in the city. While car ownership rates have increased consistently since at least 2004, according to the 2019 Continuous Household Survey, only 43% of households in Montevideo own a car.[9] This number contrasts with the 91% in the US in 2015, according to data from the US Census Bureau.

2.3. Data

Our main dataset is based on a detailed product-level database of daily posted prices compiled by The General Directorate of Commerce (DGC, by its Spanish acronym), a branch of the Ministry of Economy and Finance in Uruguay This data comprises information about

[8] See Comisión de Promoción y Defensa de la Competencia (2022). The information on trip length comes from a survey of 200 households carried out by *Equipos Consultores* in late 2020. Even for relatively large purchases of over 2500 Uruguayan pesos (some 60USD), trips of over 10 blocks do not make up more than 25% of total trips.

[9] Data from the *Encuesta Continua de Hogares* from the Uruguayan National Statistical Institute.

grocery stores all over the country. The DGC is the authority responsible for the enforcement of the Consumer Protection Law and requires retailers to report their daily prices once a month using an electronic survey. The data on prices obtained by the DGC is then disseminated on a public website that allows consumers to check prices in different stores and compute the cost of different baskets of goods across locations.[10]

The database has its origins on Resolution Number 061/006 by the DGC, which mandates that grocery stores and supermarkets report their daily prices for a list of products if they meet the following two conditions: i) they sell more than 70% of the products listed in 2007 (or 50% of the expanded product list from 2010), and ii) they either have more than four grocery stores under the same brand name or have more than three cashiers in a store. The information sent by each retailer is part of a sworn statement, and there are penalties for misreporting. The stated objective of the government with these measures is to ensure that prices posted on the website reflect the actual posted prices in the stores. In this regard, stores are free to set prices, but they face a penalty if they try to misreport them to the DGC.

The grocery prices data includes daily prices from April 1st of 2007 to December 31st of 2019 for 154 products, most of them defined by Universal Product Code (UPC). These codes allow us to track the same good in stores across locations, avoiding measurement problems resulting from the comparison of different products (see the discussion in Atkin and Donaldson 2015). The product markets for the goods included in the sample represent 15.6% of the CPI basket. Most items have been homogenized to make them comparable, and each supermarket must always report the same item under each code. For example, the Coca Cola soft drink is reported in its 1.5 liter non-returnable container variety by all stores. If this specific variety is not available at a store, then no price is reported for that good.

The three best-selling brands are reported for each product market.[11] Initial products were selected after a survey to some of the largest supermarket chains in the year 2006. Between 2010 and 2011, the list of products was updated, including some additional markets and reviewing the top-selling brands for each category. The 154 products in the current database represent more than 60 markets defined at the product category level (e.g., sunflower oil and corn oil are considered as different product markets). For a few products, the information provided in the database does not identify the goods at the UPC level; e.g., in the meat and fresh bread markets. As a consequence, we keep the 127 products that can be successfully traced as identical in different stores.

The detailed list of these goods with their UPC, and their share in the Consumer Price Index (CPI) can be found in Appendix Table A.1. A total of 54 products entered the database in 2010-2011. Therefore, we will conduct our main analysis of price effects using two samples: 1) Our *consistent sample of goods* including the 73 unique grocery products consistently present from 2007 to 2019, and 2) a *full sample* of 127 unique grocery products including

[10] See http://www.precios.uy/servicios/ciudadanos.html and Borraz et al. (2014) for a detailed description of the database. The dataset employed in this paper is an updated version of the one used in that paper and in Borraz et al. (2016).

[11] Exceptions are sugar, crackers, and cocoa, which have only two brands; and rice, which has up to six brands. Supermarket own brands are not included in the dataset.

those included in the price database in 2010.

The original price data had incomplete temporal coverage in 2007 – the first waves were disseminated in April of that year – so we limit our sample to the period 2008–2019. Prices of a subset of goods offered by three pharmacy chains were added to the DGC database in 2016. We exclude these from our sample because they are not consistently observed throughout the period.[12] Our monthly price variable for each product in a store is obtained by taking the modal (most common) price reported for the product by that store in the original daily DGC data. This helps us avoid the influence of short-term sales and discounts offered by the stores (see Eichenbaum et al. 2011) .

Several features of the DGC dataset indicate that the reporting of prices and stores is consistent over time – i.e., the absence of reported price for a specific good is more likely to arise due to the unavailability of the good at the store than due to reporting issues. The data collection by the DGC is based on an electronic survey administered automatically once a month. Changes in reporting are relatively rare: if a store is reporting the sale of a good in one month, the probability that it does so again in the consecutive month is over 96%. Conversely, if a store does not report a price in a period, the probability that it does not do so in the subsequent period is 97%. Short, one month gaps in reporting are also rare.[13] Taken together, these elements suggest that stores are prompt and consistent in complying with their reporting obligations to the DGC.

For each grocery store, we have information on its exact location, given by its coordinates, and whether it belongs to a supermarket chain. Our analysis will focus on the city of Montevideo, the capital and largest city of Uruguay, with nearly forty percent of the country's population. There are a total of 249 grocery stores and supermarkets located in urban areas Montevideo in the database. Their location is illustrated in Figure 1. In most of our analysis, we restrict attention to grocery stores located within 2km of the LVS boundary, which leaves us with a total of 135 individual stores.[14]

We complement our data on product prices by store with data on individual LVS projects from the the National Housing Agency (*Agencia Nacional de Vivienda*), register data on housing transactions taking place in Montevideo and data on the Municipal Property Registry on the stock residential units in the city and the year of completion of each building. These data are used either for descriptive purposes or – in the case of the Municipal Property Registry – to measure the year in which new units were built.

Descriptive features of the database are reported in Table 1. Descriptive statistics for annualized price changes measured over the period 2010-2019, at the level of individual good-store pairs are reported in Panel A. We report averages for the consistent sample of goods and the full sample of goods as well as for averages computed with and without CPI weights applied at the store level by product category (see section 3.1). Average annualized

[12]We will provide tests of the sensitivity of our results to both the start date and the inclusion of the pharmacy chains in the sample in Section 5.

[13]To study this, we create a balanced monthly panel at the level of store-product pairs and calculate that, across all years, the instances of 1 month gaps in reporting amount to 0.8% of observations.

[14]The number of stores varies by year due to entry and exit and opening of new branches.

TABLE 1
DESCRIPTIVE STATISTICS – STORES WITHIN 2KM OF THE LVS BOUNDARY

		Mean	Median	Std. dev.
A. Annualized % Price Changes (2010-2019)				
Balanced Basket of Goods (Unweighted)		7.7	8	2.5
Balanced Basket of Goods (Store Weights)		7.7	8	2.5
All Goods (Unweighted)		7.8	8	2.6
All Goods (Store Weights)		8	8.1	2.6
B. Varieties by Supermaket				
Number of Varieties (Balanced Basket)	2010	62.5	64	5.9
	2019	55.3	54	9.7
Number of Varieties (All Goods)	2010	99.3	104	11.1
	2019	91.5	89	14
C. Change in Newbuilding Activity				
Δ in New Built Area <1km of stores (%)		223.8	32.2	942.6
Δ in New Built Units <1km of stores (%)		178.8	54.3	586.7
D. Other Dataset Characteristics				
Total Number of Supermarkets in Dataset	2010	112		
	2019	113		
Total Number of Goods in Dataset	2010	126		
	2019	122		

Notes: Descriptive statistics for the database on grocery good prices from the DGC. Panel A represents annualized growth rates in prices calculated between 2019 and 2010 for both the basket of goods present in the sample consistently since 2008, and including goods added during 2010. Panel B represents the average number of goods in each basket across supermarkets in 2010 and 2019. Panel C represents changes in building activity taking place within 1km of stores in the sample. Sample restricted to stores within 2km of the LVS boundary in all panels. Panel D provides information on the number of grocery stores and goods in 2010 and 2019.

price changes calculated in this way vary between 7.8% and 8%. This is broadly consistent with annualized inflation between 2010 and 2019 that stood at 8.2%. Panel B displays descriptives for the number of varieties sold by each store in 2010 and 2019. Again, we report figures for the consistent sample and full sample of goods. Panel C provides figures for the changes in building activity taking place within 1km of every store in our sample. These are measured as percentage changes in the area built and the number of units between periods 2019-2013 and 2010-2004. We observe a positive average change in building activity which may be partly due to the influence of the LVS.

3. Empirical Analysis: Neighborhood Change and Retail Markets

The primary aim of our empirical analysis is to estimate the effect of the introduction of new housing stock on local grocery markets. We will be looking at three different features of these markets: the price level at local stores, the number of varieties available, and the local density of stores accessible to consumers. These are equilibrium objects depending on local demand and supply conditions. The three outcomes shape the welfare consumers obtain from participating in the local market for groceries.

3.1. Empirical Strategy

Identifying the effects of new residential stock on grocery markets is challenging because local demand for housing space can be affected by retail prices and the mix of varieties available to consumers in that location. In addition, other confounders such as ease of transport access or crime levels may simultaneously affect housing demand and grocery supplies. In order to untie these knots, we exploit the change in the spatial distribution of new residential development induced by the LVS policy. To do this successfully, we will focus our attention on the 135 grocery stores located within a two kilometer band on either side of the LVS boundary.[15] Henceforth, we will refer to regions on each side of the boundary as the LVS and comparison regions, respectively. These areas are more comparable with each other than, for example, areas in the urban periphery. Moreover, as shown in Panel A of Figure 2, it is at this scale where our quasi-experimental variation can be leveraged for estimation. Regarding longitudinal variation over time panel A of Appendix Figure A.5 plots the age of housing by year of completion for the LVS and comparison regions and clearly shows an increase in the number of units built in the LVS region after 2015.

The analysis of the effect of neighborhood change on prices and product variety relies on exploiting variation in the prevalence of newly built housing stock in the vicinity of stores. To illustrate how the LVS scheme affected changes in local housing stock, we first create a variable measuring the number of new stock taking taking place within 1km of each store over time.[16] Newly built stock is defined as stock that is 6 or less years old at the time of measurement. We use the accumulated change over time in an effort to measure changes to the density and vintage of the local housing *stock* rather than simply the *flow* change in construction in one given year. We choose six years because the first new units built under the aegis of the LVS were sold in 2013, six years before 2019. Thus, variable New Stock$_{st}$ measures the exposure of each supermarket s to new residential construction and, therefore, to changes in local demand for its goods. We estimate the following event-study specification at the store-level:

$$Log(\text{New Stock}_{st}) = \sum_{\substack{k=2008 \\ k\neq 2010}}^{2019} \rho_k Policy_s \times \mathbb{1}\{t = k\} + Policy_s + \delta_t + u_{st} \tag{1}$$

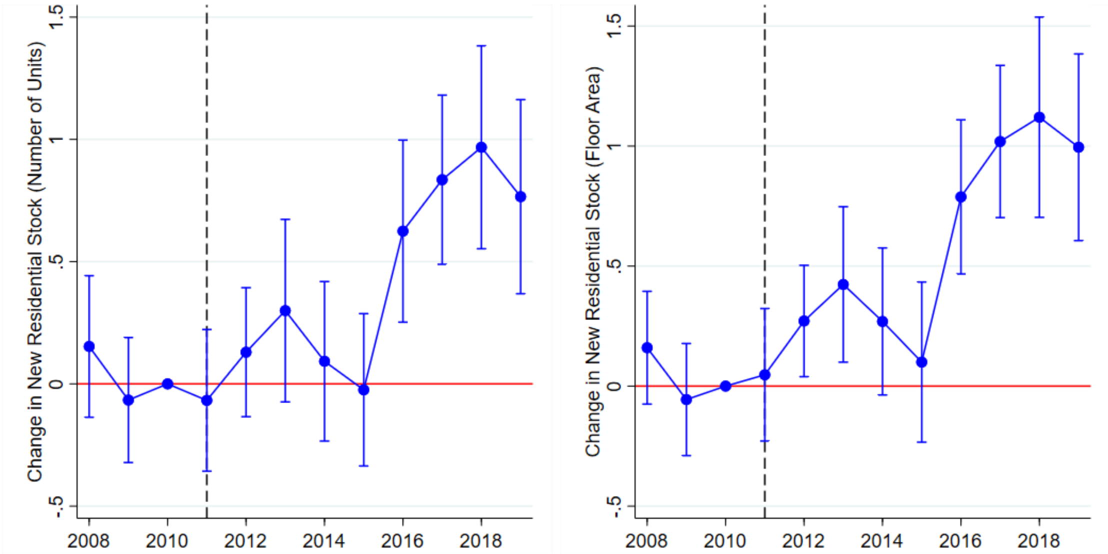
where $Log(\text{New Stock}_{st})$ is either the logarithm of the number of new units or the total floor area of these units (in m^2) measured in year t within 1km of grocery store s. Variable $Policy_s$ is an indicator taking value 1 if store s is inside the LVS region and 0 otherwise. Finally, δ_t represents time-effects for every year. The sum in the right-hand side of equation 1 includes a set of interactions between $Policy_s$ and year dummies. Therefore, coefficients ρ_k will measure the difference in newly built stock between the LVS eligible region and the comparison region relative to 2010, the year before the introduction of the policy.

[15] The band around the boundary considered in the analysis is illustrated in Figure 1.

[16] The 1km radius is motivated by the information reported in Section 2.2 indicating most consumers in Montevideo shop within 1km of their home.

FIGURE 3

TIMING OF NEW RESIDENTIAL DEVELOPMENT



(A) NUMBER OF NEW UNITS (B) FLOOR AREA OF NEW UNITS

Note: Event-study graphs for changes in new residential stock. Panel A represents estimates obtained using the number of new units as the dependent variable. Panel B represents estimates obtained using the floor area of units as the dependent variable. Round markers indicate coefficients from estimating equation 1. They measure the relative change in the presence of new stock within 1km of grocery stores between the LVS region and the comparison region for every year between 2008 and 2019. Effects are relative to 2010, the omitted year. Vertical segments correspond to 95% confidence bands. Dashed line corresponds to 2011 (the year the LVS was passed).

Estimates for the ρ_k coefficients and their corresponding 95% confidence intervals are reported in Figure 3. Three important conclusions can be drawn from this figure. The first is that the difference in the relative intensity of construction activities around grocery stores on both sides of the LVS boundary was stable before the introduction of the LVS policy. That is, there are no apparent differences in the trends followed by the intensity of new residential development around stores in the policy and comparison regions. The second conclusion is that, by the end of the period, a large and persistent difference in the presence of new housing stock has appeared, which is consistent with the descriptive evidence in section 2.1. This is the variation in housing stock that resulted from the LVS policy, and what allows us to use the policy to study the effect of neighborhood change on local retail markets.

Finally, Figure 3 shows that difference in completions across locations appeared roughly 5 years after the introduction of LVS in 2011. This is again consistent with the evidence on LVS sales shown in section 2.1. It took more than 5 years for the incentives provided by LVS to translate into new completions, largely because of the time required to produce new multi-family buildings.

3.2. Neighborhood Change and Grocery Prices

We now turn to discuss how we estimate the effect of new housing stock on local retail prices. To do so, we will use the increase in building activity on the LVS region after 2011 as an exogenous shock to the local housing stock. We begin by using our detailed price data to compare the evolution of grocery prices in stores in the LVS and comparison regions over time. For this purpose, we will use the event-study specification:

$$Log(P_{ist}) = \sum_{\substack{k=2008 \\ k\neq 2010}}^{2019} \phi_k Policy_s \times \mathbb{1}\{t=k\} + \alpha Policy_s + \delta_{it} + u_{ist} \tag{2}$$

where P_{ist} is the price of product i in store s and period t, $Policy_s$ is a dummy taking value 1 if store s is located in the tax-exempt area, δ_{it} is a full set of product-time effects that account for aggregate product-type variation in prices. Coefficients ϕ_k capture differences in the relative paths of prices for stores on both sides of the LVS boundary relative to reference year 2010. Estimation is carried out using only stores within two kilometers of the LVS boundary.

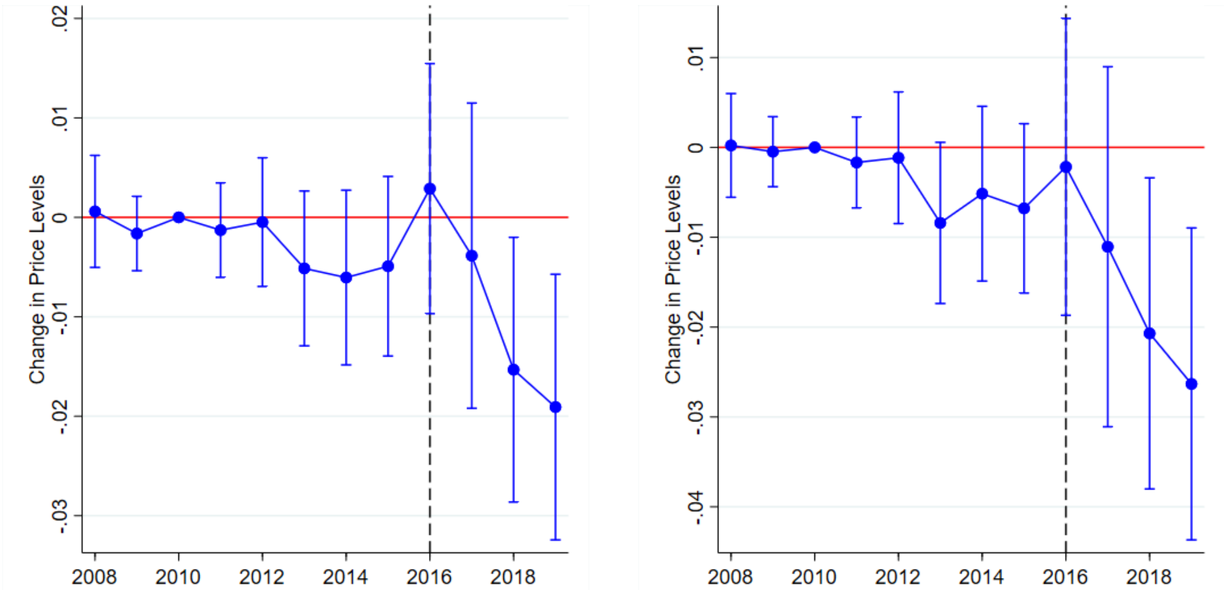
Estimates of these coefficients are reported graphically in Figure 4. Panel A represents estimates obtained using the consistent sample of goods present in the sample since 2008. Panel B represents estimates using the full sample of 127 goods. Both graphs show that the difference in grocery prices between stores in both regions around the LVS boundary was stable between 2008 and 2012. The p-value of a joint test for equality of coefficients ρ_{2008} through ρ_{2012} was above 75% in both cases. This is reassuring, as it indicates that the parallel trends assumption required for identification is plausible in our context. We observe coefficients continue to be statistically insignificant in subsequent years up to 2016. This is consistent with the fact that only a relatively small fraction of new LVS units had been effectively sold before 2016 – so the local demand faced by stores would not have been affected much by the policy yet. In 2017, we find a clear break from trend, with estimates shifting towards the larger reduced-form effects of -2% and -2.6% that we observe in 2019.

To obtain reduced-form estimates of the impact of the LVS policy on grocery prices at the end of our sample in 2019 we use a specification analogous to the one in equation 2, but replacing the interaction term $\beta_P Policy_s \times post_t$ instead of the sum across years. We estimate this parameter using data for 2010 and 2019 only, and define dummy variable $post_t$ as taking value 1 in 2019. Therefore, β_P can be interpreted as a difference-in-differences estimate capturing changes in relative prices of goods at stores on each side of the boundary over that period. An alternative to this approach is to use eligibility for the LVS tax-exemption to create an instrument for housing construction activity. We present this alternative strategy and associated results in Appendix B.

We report estimates for the effect of the neighborhood change on prices using different product-specific weights. Weighting is important because the effective price faced by households buying a bundle of goods depends on the relative share of expenditure in each product on the household budget. As we do not observe household consumption at the individual level, we cannot compute these fractions directly or study changes in the share of income devoted to each product in response to the policy. We circumvent this problem by using CPI weights of different product categories obtained from the Uruguayan National Statistical Office. As varieties of goods available may vary by supermarket and over time, we need to

Figure 4

Event-Study Graph: Prices



(A) Balanced Sample of Goods (B) Full Sample of Goods

Note: Event-study graphs for changes in price levels. Round markers indicate estimates for the sequence of ϕ coefficients in equation 2. Panel A represents estimates obtained with our sample of products consistently present in the sample from 2008. Panel B represents estimates obtained with the full sample of UPC-identifiable products. Effects are relative to 2010, the omitted year. Vertical segments correspond to 95% confidence bands. Standard errors are clustered at the store level. While the LVS program began in 2011, dashed vertical lines correspond to 2016, the year after which a large share of LVS units were sold in the housing market.

make suitable transformations to the original CPI weights if we want to use them to create appropriate baskets of goods.

We consider two alternatives. In the first place, we transform CPI weights so that the total weight of a product category for a store or supermarket corresponds to the CPI weight of that category irrespective of the number of varieties available in that store. This is quite straightforward and only requires re-scaling the CPI weights by the number of varieties available at one point in time. For a product belonging to product category k available in store s at time t we create $\omega_{kst}^{\text{store}} = \omega_k^{CPI}/n_{kst}$, where ω_k^{CPI} is the CPI weight for good category k and n_{kst} is the number of goods from category k present in our sample in period t and store s. We call these weights *store* level weights because they vary both by product category and by store.[17]

An alternative is to build weights that are fixed for every product category across all stores. We select these so as to ensure products that are more widely available receive higher weights. We calculate $\omega_{it}^{\text{global}} = \omega_k^{CPI}\left(\frac{N_{it}^k}{I_{tk} \times N_t}\right)$ where N_{it}^k is the number of stores selling product i at time t, I_{tk} is the number of varieties in product category k and N_t is the number

[17] Our definition of $\omega_{kst}^{\text{store}}$ ensures that the aggregate weight of all goods in a product category in a store coincides with the weight of k in the CPI basket. To see this, note that $\sum_{i \in \Upsilon_{kst}} \omega_{kst}^{\text{store}} = n_{kst}\frac{\omega_k^{CPI}}{n_{kst}}$, where Υ_{kst} is the set of goods of category k present in our sample for store s at time t.

of stores open at time t. We call these *global* weights because they are common for a product category across all stores. Note that if all goods are available in all stores at a point in time the global and store level weights will coincide.

Quantitative estimates of the reduced-form effects of the LVS policy on prices are reported in Table 2. Panel A provides estimates using the consistent sample of goods present in the DGC database from the beginning of the sample period, and Panel B provides estimates for the full sample of goods. Across columns, we vary the product-level weights. Column 1 reports estimates obtained using an unweighted specification. Columns 2 and 3 report estimates using CPI store-level product weights and global product weights, respectively. We find *negative* and significant reduced-form effects on prices across the board, indicating that grocery stores located in the subsidized side of the LVS boundary reduced prices by between 2% and 2.6% relative to those in the comparison region.

TABLE 2
NEIGHBORHOOD CHANGE & GROCERY PRICES

	(1) Log(Price)	(2) Log(Price)	(3) Log(Price)
A. Consistent Sample of Goods			
Policy × Post	-0.023***	-0.020**	-0.025***
	(0.008)	(0.008)	(0.008)
CPI Weights	No	Store	Global
Obs.	131493	131493	131493
B. Full Sample of Goods			
Policy × Post	-0.026***	-0.023***	-0.023***
	(0.009)	(0.008)	(0.007)
CPI Weights	No	Store	Global
Obs.	181146	181146	181146

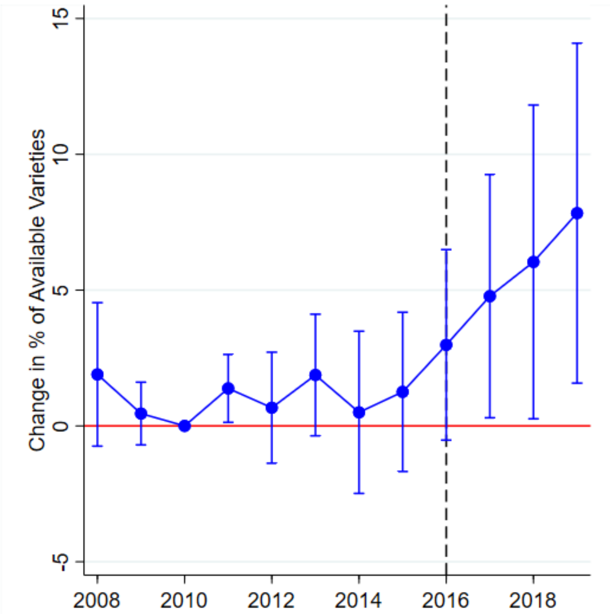
Notes: Estimates based on product-store-month regressions using years 2010 and 2019. The outcome variable in all specifications is the logarithm of the price of the product price. Panel A represents estimates obtained with our sample products of consistently present from 2008. Panel B represents estimates obtained with the full sample of products. Estimates in column 1 are obtained without using product weights. Estimates in column 2 are obtained using store-level product weights based on CPI weights. Estimates in column 3 are obtained using global product weights based on CPI weights. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

3.3. Neighborhood Change & Product Varieties

We now turn to test whether the introduction of new housing stock induced by the LVS policy led to an increase in varieties available to consumers locally. We measure varieties at the store level, by computing variable Variety share$_{st}$ defined as the percentage of reported products included in our price database that are offered at store s and year t.

We first report yearly coefficients akin to those reported in Figure 4, using the share of available varieties as the outcome in a grocery store panel with interacted year effects. Coefficients for these interaction terms are illustrated in Figure 5, with effects being relative to 2010, the base year. As in the case of prices, we do not observe substantial changes in varieties available between both sides of the LVS boundary in the period between 2008 and 2012. We cannot reject the null that the coefficients for this period are equal to each other (p-value 16%). A substantial change is observed starting in 2016. Note that this coincides with the period in which we observe the break for new build stock. The coefficients for 2016 through 2019 are increasing and large relative to those observed in the previous periods, indicating an increase in varieties available for local consumers coinciding with the change in housing stock.

FIGURE 5
EVENT-STUDY GRAPH: VARIETIES



Note: Event-study graph for changes in the percentage of available varieties. Round markers indicate estimated coefficients from a regression of the share of available varieties at the store level, measured in percentage points, on interaction terms between $Policy_s$ and year dummies featuring store and time effects. The outcome is measured using the full sample of goods in the DGC dataset. Effects are relative to 2010, the omitted year. Vertical segments correspond to 95% confidence bands. Standard errors are clustered at the store level. While the LVS program began in 2011, the dashed vertical line corresponds to 2016, the year after which a large share of LVS units were sold in the housing market.

To obtain the reduced-form estimates of the effect of the change in housing stock on available varieties, we estimate

$$\text{Variety share}_{st} = \beta_V Policy_s \times post_t + \delta_t + \alpha Policy_s + \epsilon_{st}$$

Estimates of β_V are reported in Table 3. Column 1 reports estimates obtained using the consistent sample of goods present in the DGC database since 2008 and column 2 reports estimates obtained with the full sample of goods. In both cases, we find that the share of available varieties offered by stores in the LVS region increased in 7 percentage points relative to the variety share offered in the comparison region. We discuss IV estimates of the elasticity of the variety share to new housing stock in Appendix B.

The estimates in Figure 5 and Table 3 indicate that there was an expansion in product

TABLE 3
NEIGHBORHOOD CHANGE & PRODUCT VARIETIES

	(1)	(2)
Policy × Post	0.066**	0.072**
	(0.032)	(0.033)
Sample of Goods	Consistent Sample	Full Sample
Obs.	212	212

Notes: Estimates based on store-month regressions using years 2010 and 2019. The outcome variable in both specifications is the share of available varieties at the store level, measured in percentage points. Estimates in column 1 are obtained with our sample of products consistently present in the sample from 2008. Estimates in column 2 are obtained with the full sample of products. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

variety available locally to households in the LVS region. All else equal, the expansion of the choice set would constitute an improvement in local retail conditions available to customers.[18]

3.4. *Neighborhood Change, Access to Stores and Entry*

The neighborhood change induced by the LVS policy can affect the entry and exit of stores. Resulting changes in store density can influence the ease with which residents can shop for groceries locally. To study the impact of the policy on grocery store access, we first compute two variables at the census tract level measuring the local store density in each year t.[19] We first create variable Grocer Access_{ct}^{1km} measuring the number of grocery stores open within 1km of the centroid of census tract c in year t. Alternatively, we consider variable

$$\text{Grocer Access}_{ct}^{1/d} = \sum_{s=1}^{S} \frac{D_{st}}{d_{cs}} \tag{3}$$

Grocer $\text{Access}_{ct}^{1/d}$ is an inverse-distance weighted average of access to grocery stores computed for each census tract c in every year t. S is equal to 249, the total number of stores in the urban areas of Montevideo, variable D_{st} is a dummy taking value 1 if grocery store s was active in year t, and d_{sc} is the Euclidean distance between store s and census tract c. In the case of both Grocer Access_{ct}^{1km} and Grocer $\text{Access}_{ct}^{1/d}$, high values indicate access to a larger number of stores. Using both of these variables and a census tract panel covering the period 2008-2019, we estimate the event-study specification:

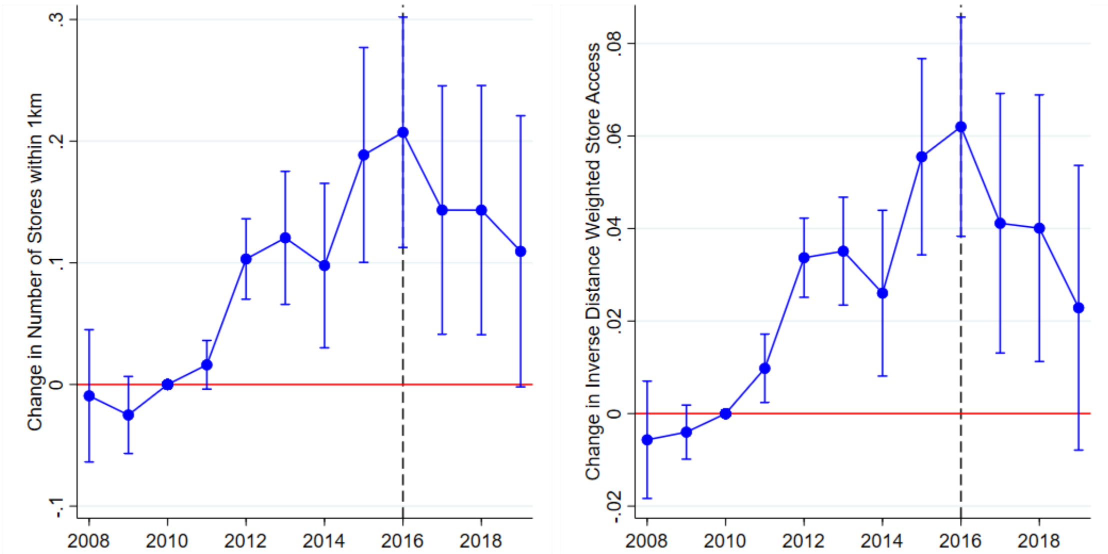
$$Log(\text{Grocer Access}_{ct}) = \alpha_c + \delta_t + \sum_{\substack{k=2008 \\ k\neq 2010}}^{2019} \psi_k Policy_c \times \mathbb{1}\{t=k\} + \varepsilon_{ct} \tag{4}$$

[18] One possible concern is that the expansion of varieties could come from the addition of relatively low quality, budget varieties. Coupled with particular changes in relative prices across the quality distribution, this could imply a worsening of retail conditions for households. Evidence in section 5 below indicates this change in relative prices by quality is not observed in our data.

[19] Census tracts are relatively small geographies, with a total of 969 areas in the Montevideo, and over 450 areas within 2km of the LVS region boundary.

where $Policy_c$ is a dummy taking value 1 if census tract c is located in the LVS policy region, α_c is a census tract fixed effect and δ_t represents year effects. The resulting estimate of ψ_k will be positive if the difference between grocery store access in the policy and comparison regions is positive relative to reference year 2010. In order to accommodate for the role of spatial dependence when conducting inference, we cluster at the level of $0.01^o \times 0.01^o$ cells. This leaves us with a total of 60 spatial clusters in the sample of census tracts within 2km of the LVS boundary.

FIGURE 6
EVENT-STUDY GRAPH: ACCESS TO STORES



(A) STORES WITHIN 1KM (B) DISTANCE-WEIGHTED STORE ACCESS $(1/d_{cs})$

Note: Event-study graphs for changes in access to stores. Panel A represents estimates obtained using the logarithm of the number of stores within 1km as the dependent variable. Panel B represents estimates obtained using the logarithm of the inverse distance weighted store access as the dependent variable. Round markers indicate estimated coefficients from a census tract level regression of grocery shop access on interaction terms between $Policy_c$ and year dummies featuring census tracts and time effects (see equation 4). Effects are relative to 2010, the omitted year. Vertical segments correspond to 95% confidence bands. While the LVS program began in 2011, dashed vertical lines correspond to 2016, the year after which a large share of LVS units were sold in the housing market.

Figure 6 plots the sequence of ψ coefficients obtained when using the log of the number of stores within 1km (left panel) and the log of the inverse-distance weighted number of stores (right panel) as outcomes. We can observe that the introduction of the LVS policy did lead to an increase in local access to stores after 2011. Differential changes in access to stores peaked in 2016 and then dropped in the following years. Note that much of this change took place before the LVS units came in the market, perhaps due to anticipation effects for retailers. By 2019 the change in grocery access had tapered off somewhat, becoming only marginally significant in both graphs, in line with the results for reduced-form coefficients reported in Appendix Table A.3. Instrumental variable estimates of the effects of new stock on store access are discussed in Appendix B and are in-line with these findings.

It is worth mentioning that the increase in store access cannot by explained by increases in net entry by stores in the LVS region. As shown in Panel D of Appendix Figure A.5, the total number of stores in this region did not increase between 2011 and 2019. Therefore, observed increase in convenience are related to changes in the spatial distribution of stores rather than to net entry.

In any case, the results in Figure 6 suggest that the anticipated change in housing stock in neighborhoods affected by the policy influenced patterns of entry and exit in such a way that accessibility to stores experienced a relative increase throughout much of the period after 2011. This would result in a mild increase in convenience for households shopping in these neighborhoods. Combined with the reduction in price levels and an increase in product variety reported in the previous sections, these findings indicate that neighborhood change resulted in a net improvement in the conditions for grocery consumers at the local level. In the next section, we discuss the mechanisms that could lead to these combined outcomes.

4. Discussion

We can interpret the construction of new housing stock induced by the LVS policy as an increase in local demand in the market for groceries. Under this interpretation, our finding that grocery stores near the new developments reduced good prices appears counter-intuitive: a conventional supply and demand framework would make the opposite prediction in the face of an increase in demand.[20] Yet, this conventional framework may not be appropriate if other margins in the local supply of groceries can also respond (see e.g., Jaravel 2018).

In this section, we first introduce a theoretical framework featuring endogenous prices, product variety and entry, in which an increase in demand leads to responses in supply that can rationalize the empirical results in the previous sections. We then present complementary evidence on the role of new entrants and incumbents in the supply response to the local demand shock brought about by neighborhood change. Finally, we discuss the potential role of changes in supply of commercial space associated to new multi-family developments as an alternative explanation for the change in local retail markets.

4.1. Theoretical Framework

The trade literature on multi-product firms shows that an increase in market size can decrease prices, keeping the number of varieties constant (see Mayer et al. 2014). Separate work in the industrial organization literature (Ellickson, 2007) has shown that supermarkets increase the quality of the product offered when the market size increases. We draw on these intuitions when interpreting the price effects described in the previous sections as resulting from an increase in local demand for grocery stores' goods. This increase in local demand can arise via two channels. In the first place, the building of new multi-family units increases local densities and, therefore, the number of people living within existing store's local markets. In the second place, the fact that these units are new and generally of high

[20]This prediction is confirmed, for example, in recent work in Handbury and Moshary (2021) which reports a decline in grocery prices in response to a negative shock specific to breakfast and lunch product demand.

quality (see section 2.1) implies they will attract relatively high income residents.[21] Evidence of positive spillover on housing prices are reported in González-Pampillón (2021).

To rationalize how an increase in local demand can result in lower prices, we propose a framework based on Mayer et al. (2014) where equilibrium prices are affected by number of offered varieties and entry of new competitors.[22] In our framework, changes in the scale of a market (i.e. the number of consumers available) result in lower prices via either of these channels.

There are L identical consumers with individual utility:

$$U = q_0 + \alpha \sum_j q_j - \frac{1}{2}\gamma \sum_j (q_j)^2 - \frac{1}{2}\eta \left(\sum_j q_j \right)^2 ,$$

where q_0 and q_j represents the individual consumption of the *numeraire* good and each variety j, respectively. The demand parameters α, γ, and η are all positive. Note that these preferences feature satiation points, i.e. utility becomes decreasing in q_j for large enough values of q_j. Maximizing utility we obtain the individual inverse demand for each variety:

$$p_j = \alpha - \gamma q_j^c - \eta Q. \tag{5}$$

where q_j^c is the individual consumption of good j and $Q = \sum_{i=1}^{N} q_i^c$, so the sum of individual consumption of all available varieties.

Production is carried out by identical firms that compete in quantities. In equilibrium, the relationship between individual consumption q_j^c and the supply by each firm q_j^m are given by $q_j^c = \frac{\sum_{k=1}^{M} q_j^k}{L}$, where M is the number of firms in this market. Substituting in individual demand, we obtain the demand function for each variety as a function of firm quantities q_j^k:

$$p_j = \alpha - \gamma \frac{\sum_{k=1}^{M} q_j^k}{L} - \eta \frac{\sum_{k=1}^{M} \sum_{j=1}^{N} q_j^k}{L} \tag{6}$$

Firms face entry costs F, fixed costs of offering each variety F_N and fixed marginal costs per unit c, with $c < \alpha$.[23] When considering the multi-firm equilibrium, we consider firms first entering simultaneously, then simultaneously choosing the varieties to be produced, and then simultaneously choosing quantities for each variety. Firm profits are therefore given by $\pi^m = \sum_{j=1}^{N_j} \left[q_j^m \left(p_j^m - c \right) \right] - F - F_N N$. Substituting the demand into the profit function, we can set up firm m's problem in the final stage (when choosing the quantity of each variety q_j^m:

[21] In our formal description below, we abstract from changes in local consumer types and simply treat this as a change in the scale of the market.

[22] A model using similar preferences has been recently used by Benkard et al. (2021) to explain the change in concentration in US product markets.

[23] We can think of F_N as the fixed costs of sourcing and advertising each variety, and the cost of space associated to placing each variety at the store.

$$\max_{\{q_j^m\}_{j=1}^N} \sum_{j=1}^{N} \left[q_j^m \left(\alpha - \gamma \frac{\sum_{k=1}^M q_j^k}{L} - \eta \frac{\sum_{k=1}^M \sum_{i=1}^N q_i^k}{L} - c \right) \right] - NF_v - F$$

Taking first-order conditions for this problem and solving for q_j^m we obtain the reaction function for variety j sold by firm m. These depend on the values of q_i^m for other varieties $i \neq j$. The specific functional form of this dependence derives from our choice of preferences, as do the results below.

We can use this framework to provide two comparative statics results, where we show how equilibrium prices, varieties or the number of firms vary with the number of consumers L. These are presented in Propositions 1 and 2.

Proposition 1 - Market size, varieties and prices

Consider the problem of a monopolist choosing varieties and prices. In this case, a large enough increase in L results in an increase in endogenous varieties N and a reduction in the price of infra-marginal varieties.

Proof: See C.1.

The proof proceeds by obtaining an expression of firm profits as a function of varieties N. After characterizing the optimal number of varieties selected by the monopolist in this context N^*, we show this quantity increases with market size L (for sufficiently large changes in L). Finally, we show that this will result in a reduction in the markups for sold goods. Thus, we show that an expansion in the market for a retailer can lower prices via an expansion in varieties. It is worth noting that this mechanism relies on using preferences for which the product-level elasticity of demand increases (in absolute value) with the varieties of good available – i.e., additional varieties generate suitable substitutes for existing goods. We believe this is a reasonable assumption in the context of grocery markets.

Proposition 2 - Market size, entry and prices

Consider now the case in which the number of firms is endogenous. For a fixed number of varieties N, larger values of L result in more entry and lower equilibrium prices.

Proof: See C.2.

The proof proceeds by obtaining an expression for total firm profits as a function of the number of firms M. We characterize the equilibrium number of firms M^* and show that this figure is increasing in L. We also show that equilibrium prices are themselves decreasing in M^*, so that an increase in demand can lead to lower prices via its effects on entry, even if the number of varieties is fixed.

We have shown that both changes in varieties available or entry can provide the supply response that accompany the reduction in prices resulting from an increase in demand. We discuss the role of these two margins of adjustment in the following.

4.2. Response of Incumbents and New Entrants

To investigate in detail how the local supply conditions changed in response to the change in supply we can study differences in the price levels and product varieties offered by continuing incumbents and new entrants in the LVS region.

Changes in the price and product variety offered by incumbents give us information on the pro-competitive effect resulting from the local increase in housing stock (Atkin et al., 2018). To explore this empirically we restrict the sample to *continuing stores* – i.e., stores that were consistently present between 2010 and 2019 – and reproduce our event-study graphs for both outcomes of interest. Results are illustrated in Figure 7 (quantitative estimates using data for 2010 and 2019 are reported in Appendix Tables A.4 and A.5). We can observe that, for both outcomes, the effect of the policy on continuing stores is almost identical to that observed in the full sample. A first implication is that the effect of a change in demand induced by the policy is consistent with the response described in Proposition 1, where the incumbent reduces prices and increase varieties. An increase in varieties and prices can result from an increase in demand because in our framework varieties are substitutes for each other, and their increased availability increases the price elasticity of demand for each variety. Thus, stores will accompany the increase in product variety with a reduction in prices, reducing markups.

The results in Figure 7 also allow us to rule out that the entry of larger chains with more market power in the wholesale market is the sole explanation for our findings. If all of the price and variety effects comes from the entry of chain stores with monopsony power, we should not observe a reduction in prices in continuing stores. The fact that we do is evidence *against* this explanation.

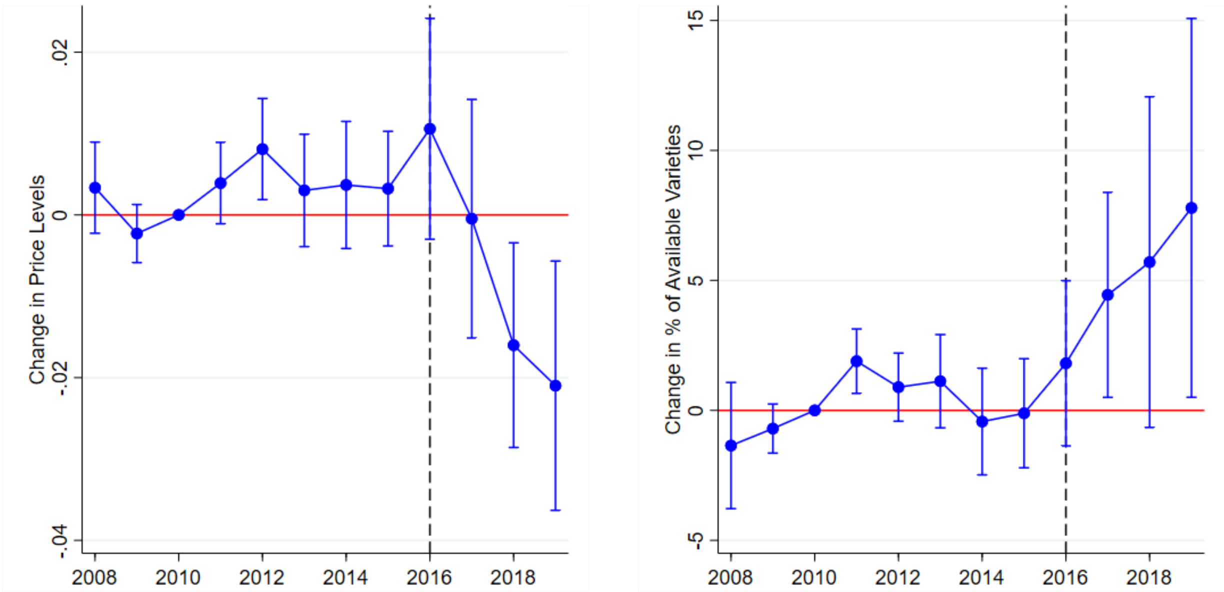
We now turn to discuss the role of new entrants in determining the improvement of local retail conditions in the LVS region. In the first place, it is important to highlight that net entry was modest in this period. There was no change in the total number of stores in the LVS region within 2km of its border between 2011 and 2019, and only a very small change in the comparison region (see Panel D of Appendix Figure A.5). It is therefore unlikely that the improvement in local retail conditions resulting from the LVS policy was driven by a change in the number of sellers: the mechanism emphasized in Proposition 2 of the theoretical framework cannot explain our findings.

Even if the number of stores is stable, store entry and exit can affect local retail conditions if the types of stores that enter are different from the incumbents or the stores that exit. For example, if small convenience stores are progressively replaced by large supermarkets this will affect the competitive conditions for both entrants and incumbents, even without a change in the total number of stores.[24] To investigate this possibility, we first estimate an event-study specification similar to the one in 4 but using as an outcome the average number of cash registers in stores within 1km of each census tract c in year t. This variable is a proxy for the size of grocery stores available locally and is measured at the time in which a store enter the dataset. Hence, it only captures changes in the size of stores resulting from entry and exit and not changes in the size of existing outlets. Results are reported in Figure 8 and indicate that there was no systematic difference induced by entry and exit on the size of stores available locally.

[24] Previous evidence suggests this can happen. In their study of the US market, Glaeser et al. (2020) find evidence that gentrification increases the number of retail establishments, but it also triggers business closures.

Figure 7

Event-Study Graphs: Continuing Stores



(A) Prices (B) Product Varieties

Note: Event-study graphs for changes in price levels and the percentage of available varieties using the sample of continuing stores (i.e., stores that were consistently present between 2010 and 2019). In Panel A, round markers indicate estimates for the sequence of ϕ coefficients in equation 2, restricting the sample to continuing stores. In Panel B, round markers indicate estimated coefficients from a regression of variety shares on interaction terms between $Policy_s$ and year dummies featuring store and time effects, restricting the sample to continuing stores. Effects are relative to 2010 the omitted year. Vertical segments correspond to 95% confidence bands. While the LVS program began in 2011, dashed vertical lines correspond to 2016, the year after which a large share of LVS units were sold in the housing market.

Finally, we investigate cross-sectional differences in prices and product variety between stores depending on entrant status using data for 2019. The fact that we focus on data for 2019 alone means this analysis will not use the same identification strategy than the main analysis in the paper (because we are not leveraging time variation induced by the LVS policy). Nonetheless, results can be of interest to investigate the degree to which turnover in local stores drives the findings in Section 3. In the case of prices, we estimate:

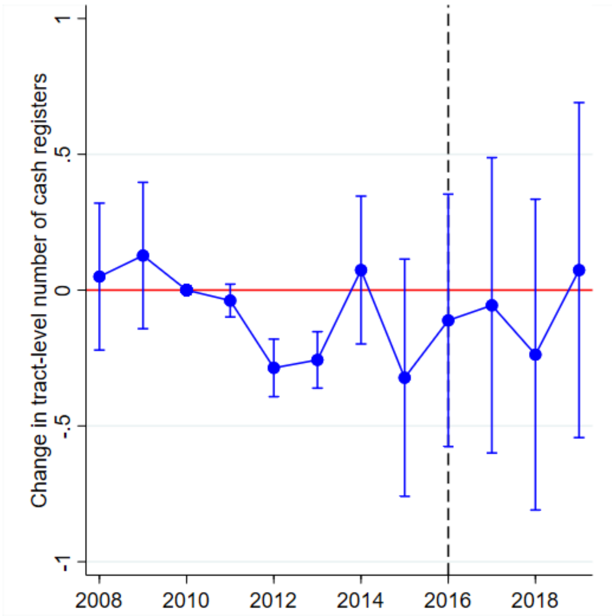
$$Log(P_{ist}) = \beta_1 \text{New}_s + \beta_2 Policy_s + \beta_3 Policy_s \times \text{New}_s + \delta_{it} + \varepsilon_{ist}$$

where dummy variable New_s takes value 1 if store s was not present in 2010, δ_{it} is a full set of product-month dummies and the other variables are defined as above. We also estimate a similar specification at the store level for product variety.[25] We report separate estimates of this model excluding and including the interaction term between New_s and $Policy_s$ in Appendix Tables A.6 and A.7, corresponding to prices and product variety, respectively. Both

[25] In the case of product varieties, the specification is given by:

$$\text{Variety share}_{st} = \beta_1 \text{New}_s + \beta_2 Policy_s + \beta_3 Policy_s \times \text{New}_{is} + \delta_t + \varepsilon_{st}$$

FIGURE 8
EVENT-STUDY GRAPH: NUMBER OF CASH REGISTERS IN NEARBY STORES



Note: Event-study graphs for changes in tract-level number of cash registers. Round markers indicate estimated coefficients from a average store size (number of cash registers) within 1km of a census tract on interaction terms between $Policy_c$ and year dummies featuring census tract and time effects. Effects are relative to 2010, the omitted year. Vertical segments correspond to 95% confidence bands. The dashed line corresponds to 2016, the year after which a higher share of LVS housing started being sold.

tables suggest that is is unlikely that new entrants can explain our findings. These outlets typically charge higher prices and sell less varieties than incumbents (though the coefficients for varieties are not significant at conventional levels).

Collectively, the findings in this section indicate that the effects of neighborhood change on local grocery markets operate through a reduction in prices and an increase in product variety by incumbent firms. In light of our theoretical framework, we interpret these changes as an equilibrium response to an increase in local demand.

4.3. New Development & the Supply of Commercial Space

We interpret the neighborhood change resulting from the LVS policy as an increase in the local demand for groceries. Yet in Montevideo, as in other cities, it is not uncommon for multi-family developments to incorporate commercial space on the ground floor. The residential development projects built under the LVS were no exception, with roughly 30% of developments including commercial space. This can be consequential if the commercial space in these buildings either increases the number of grocery stores available locally or affects the local price of commercial land via an increase in supply. In that context, the improvement in local retail conditions could be the result of changes in supply, not demand.

To rule out this possibility, we make three different points. First, as argued above, the scale of entry in the LVS region, as measured by the number of stores in the DGC data, is very limited. This limits the concern arising from the effect of new commercial space on entry of new stores.

Secondly, the scale of entry of small grocery stores that are not featured in the DGC data is limited. We identified which LVS developments have grocery stores on their ground floors using an in-person visit to completed developments.[26] We complemented these visits with queries on the opening dates of these stores. Only 4 small grocery stores in LVS developments were not present in our dataset and had opened before 2019, with two opening in 2018 and two in 2017. Three of these stores belong to a chain of small groceries with at most two cashiers and a small coverage of standard varieties, meaning they did not meet the eligibility criterion for inclusion in the DGC database. It appears unlikely that this limited level of entry would have had strong effects on price levels and product variety offered by incumbent stocks. This is especially the case if we note that its impact on our measures of household store access is limited.[27]

Finally, we conduct a complementary analysis to rule out remaining concerns regarding the impact of expanded commercial space associated with LVS developments on retail markets. For this purpose, we create dummy variable Commercial_s which identifies stores that are within 1km of the location of an LVS development featuring commercial premises. This variable takes value 1 in roughly 50% of stores in the LVS area. Using this variable, we estimate:

$$Log(P_{ist}) = (\beta_P Policy_s + \gamma \text{Commercial}_s) \times post_t + \alpha_1 Policy_s + \alpha_2 \text{Commercial}_s + \delta_{it} + u_{ist} \quad (7)$$

where the inclusion of interaction term $\text{Commercial}_s \times post_t$ will capture the degree to which LVS projects with commercial space are behind the reduction in prices documented above. Estimates for both interaction terms in equation 7 are reported in Table 4. Estimates of coefficient β_P in this specification are somewhat *larger* in absolute value than those reported in our baseline results. Analogous estimates for varieties are reported in Appendix Table A.8. Both results indicate that changes in the supply of commercial space induced by the policy were not responsible for its effect on grocery markets.

5. Robustness Checks & Placebos

In this section, we provide a series of additional tests to evaluate the robustness of our findings. We will consider how our main results are affected by i) different choices of weights, ii) using an alternative baseline year, iii) varying the bandwidth around the LVS boundary used to define the sample, iv) estimating price effects separately for low- and high-price

[26]The in-person search was carried out in May 2022.

[27]We reproduce the event-study graph for store access when including these 4 stores in Appendix Figure A.6. Point estimates of the LVS coefficients obtained when incorporating the additional stores after 2016 are higher. This is expected, given that these grocery stores enter in the LVS region. With these values, we can conclude that the long-term effect of neighborhood change on store access is positive at conventional levels. Yet the difference in coefficients relative to the case in which these stores are not counted is small and insignificant.

Table 4

Price Effects – Controlling for Addition of Commercial Space

	(1)	(2)	(3)
Policy × Post	-0.033***	-0.030***	-0.029***
	(0.011)	(0.008)	(0.009)
Commercial LVS × Post	0.015	0.012	0.012
	(0.010)	(0.008)	(0.008)
CPI Weights	No	Store	Global
Obs.	181146	181146	181146

Notes: Estimates based on product-store-month regressions using years 2010 and 2019. The outcome variable in all specifications is the logarithm of the price of a good. Estimates in columns 1 are obtained without using product weights. Estimates in columns 2 are obtained using store-level product weights based on CPI weights. Estimates in columns 3 are obtained using global product weights based on CPI weights. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

brands, and v) estimating the effects on prices and product variety when including pharmacies in the sample. We also consider a series of placebo tests which rely on creating artificial areas obtained by shifting the location of the boundary in the LVS policy eligibility areas.

5.1. *Robustness Checks*

We begin by considering the robustness for our results to different analytical choices. We begin by reproducing our event-study graph for prices when varying the types of weights used, the expansion of our sample to include the available months in 2007 (April to December) in our price dataset, and an alternative specification including product-brand specific time effects. In all cases, we obtain results that are very similar to those reported in our main analysis.

In Table 5, we report reduced-form estimates to illustrate the robuestness of the reduced-form effects of the policy on prices. In Panel A, we use two alternative baseline years, 2008 and 2012. Estimates are still significant and magnitudes do not change considerably relative to those reported in columns 1 and 2 of Table 2. In panel B, we consider alternative bands around the LVS boundary when defining our sample. Columns 1 and 2 present results using a 1.5km band, while columns 3 and 4 present results using a 2.5km band. Coefficients are also similar to those obtained in our main analysis.

Appendix Tables A.9 and A.10 repeat these robustness checks for our results on varieties and store access. In case of product varieties, estimates range from 6.5% to 7.6%, very similar to our baseline estimate of 7.2%, and being statistically significant at the 5% level in all cases.

In the case of our results for store access, comparing Appendix Table A.3 and with Panel A of Table A.10 we can observe that changing the reference year to 2012 eliminates any positive effect of the LVS policy on store access. This is no surprise as most of the change in the level of store access observed in Figure 6 had already taken place by 2012. Panel B indicates that the point estimates obtained for improvement in store access are not particularly sensitive to the choice of bandwidth around the LVS border when selecting the sample. Taken together, these

TABLE 5
ROBUSTNESS CHECKS - PRICE EFFECTS

	Baseline Year: 2008		Baseline Year: 2012	
A. Alternative Baseline Year				
Policy × Post	-0.027***	-0.021***	-0.025***	-0.019***
	(0.009)	(0.007)	(0.009)	(0.007)
CPI Weights	N	Y	N	Y
Obs.	164701	164701	220936	220936
	1.5km Band		2.5km Band	
B. Bandwidth Around Boundary				
Policy × Post	-0.021**	-0.019**	-0.020***	-0.018**
	(0.009)	(0.008)	(0.008)	(0.007)
CPI Weights	N	Y	N	Y
Obs.	109809	109809	141343	141343

Notes: Estimates based on product-store-month regressions. The outcome variable in all specifications is the logarithm of the price of a good. Panel A represents estimates obtained using 2008 as the baseline year (columns 1 and 2) and 2012 as the baseline year (column 3 and 4). Panel B represents estimates obtained using stores within 1.5km (columns 1 and 2) and 2.5km (columns 3 and 4) of the S-U border. Sample used in panel B uses data for 2010 and 2019. Estimates in columns 1 and 3 are obtained without using product weights. Estimates in columns 2 and 4 are obtained using store-level product weights based on CPI weights. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

results indicate that our finding of a positive effect of neighborhood change on store access do not depend on the bandwidth around the boundary, though most of this changed happened immediately after the policy was introduced and years before the change in demand resulting from it could materialize.

As an additional check on our results, we use the data goods to explore whether the price effects documented in section 3 are concentrated on a particular subset of products within stores. In Appendix Table A.11, we estimate price effects separately for low- and high-price brands. As explained in Section 2.3, our database includes the three best-selling brands for each product market. We use variation in prices within product categories to define the high-price brand as the one with the highest average price across brands. Our definition of a high-price brand is likely to coincide with the definition of leader-brand. The remaining brands are then defined as low-price brands for exposition purposes. Results using store weights show a 2.3% reduction in the high-price brand and a similar decrease in low-price brands, with point estimates not being statistically different from each other. The improvement in retail conditions documented in Section 3 is not limited to an improvement in access to low quality or standard varieties. Moreover, these findings have equity implications if households with different incomes consume products from different segments. As far as these issues are concerned, we do not observe substantial differences by segment.

In our main analysis, we exclude pharmacies from the DGC sample. The reason is that most of these pharmacies where included in the sample after a methodological change in 2016, so we do not observe prices before that year. Appendix Tables A.12 and A.13 shows that including these stores in our sample has no impact of our qualitative findings for either prices or product variety.

5.2. Placebos

We can use the spatial nature of our empirical strategy to build a series of placebos. First, we construct a placebo border by shifting the original policy border southward until splitting the unsubsidised area U into two sub areas labelled as *Upper Placebo* and *Lower Placebo*. We can then use stores located in the unsubsidised area U, and we treat the *Upper Placebo* area as the placebo policy region to test whether differences between these regions emerge in our outcomes of interest (see Figure A.9 for a graphical description). This first exercise is labeled as placebo *South* because that is the direction in which we displace the policy boundary. Results for retail prices are presented in columns 1 and 2 of Table 6, while results for varieties are presented in column 1 of Appendix Table A.14.

TABLE 6
PLACEBO - PRICES (REDUCED-FROM ESTIMATES)

	(1) Log(Price)	(2) Log(Price)	(3) Log(Price)	(4) Log(Price)
Post $\times$ Placebo	-0.000 (0.009)	0.003 (0.008)	-0.000 (0.010)	0.005 (0.008)
Weights	N	Y	N	Y
Placebo	South	South	North	North
Obs.	60433	60433	42658	42658

Notes: Estimates based on product-store-month regressions using years 2010 and 2019. The outcome variable in all specifications is the logarithm of the price of a good. Columns 1 and 2 correspond to the placebo obtained by shifting the LVS boundary south. Columns 3 and 4 correspond to the placebo obtained by shifting the LVS boundary north. Estimates in columns 1 and 3 are obtained without using product weights. Estimates in columns 2 and 4 are obtained using store-level product weights based on CPI weights. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

The second exercise – labeled as placebo *North* – is constructed by shifting the policy border northwards up to the centroid of the LVS subsidised area S (see Figure A.8 for a graphical description). In this case, we restrict our sample to stores within two kilometers of the artificial border which lie within the LVS area S. We build a binary variable that takes the value of one for stores located in the northern part of the placebo region and use this sample to test for differences in prices and varieties within regions. Results for prices of this placebo are reported in columns 3 and 4 of Table 6, and for varieties are reported in column 2 of Appendix Table A.14. All placebos yield statistically insignificant effects and point estimates that are substantially lower than those reported in our main analysis.

6. Conclusions

Neighborhoods are shaped by their physical characteristics, with an essential role played by housing in particular. Consequently, the introduction of new housing stock can induce a process of neighborhood change. Our results show that changes induced by large scale residential development activity affect the market for groceries faced by incumbent households. Specifically, we find evidence of a moderate *reduction* in grocery prices as a response to this change in demand induced by new housing development. This is accompanied by a substantial increase in available varieties for local residents.

Using our theoretical framework, we show that these two facts can jointly arise in the context of a multi-product firm choosing what to produce: an increase in demand can prompt an expansion in the number of varieties offered and a reduction in prices. The model can be used to show that the reduction in prices can also result from the entry of new stores. Yet we do not find robust evidence of a sustained increase in the number of stores available locally as a result of the increase in housing stock. The adjustment in prices and varieties reported in Section 3 arise from changes by incumbent stores in the face of a change in local demand conditions.

The combination of a reduction in prices and an increase in varieties for fixed – or increasing – store density corresponds to a net improvement in the conditions for grocery consumers at the local level: Consumers can buy cheaper goods without a loss in the convenience of local access. Therefore, our results emphasize advantages of new development and neighborhood change for incumbent residents that have been largely overlooked by the literature. Moreover, they cast doubts on the risks that retail gentrification could pose for incumbent residents and their access to affordable groceries.

Our focus on conventional grocery goods – such as salt, soap, noodles, etc – implies that the changes in prices and varieties studied here will be especially relevant for low and middle-low income households for whom these goods amount to a larger share of their usual consumption basket. This makes our findings particularly relevant for the debate around the distributional consequences of neighborhood change. That being said, the fact that disaggregated spending data is not available in this context means we are unable to formally characterize the distributional impacts of these changes for different income groups. Efforts in this direction – which could follow recent developments in the study of inter-city differences in cost of living – remain an interesting avenue for future research.

Some final remarks are due regarding the external validity of our findings and, specifically, their *transportability* to other contexts (Pearl and Bareinboim, 2014). The use of the LVS policy as a source of exogenous variation yields clear advantages in terms of internal validity – it opens the space for a credible empirical strategy. The implications for external validity associated to this strategy are, as usual, less obvious. Most parameters of interest in this study are estimated off of variation in the development of multi-family buildings marketed to middle-high income households. Extrapolating our findings to the development of single-family neighborhoods or public/social housing may not be warranted. A different question is whether the mechanisms emphasized here can operate in general. The margins of adjustment of grocery supply will be available in most cities where stores can vary the number of varieties offered, for example by expanding their premises. Market structure may also be relevant. In Montevideo, the grocery market is characterized by the presence of three large supermarket chains and a large number of players operating smaller stores (Borraz et al., 2016). Thus, the market structure in our context is comparable to that observed in other middle-sized cities in middle and high-income countries which retain a competitive fringe of independent stores. Keeping in mind these considerations, we remain optimistic about the replicability of our findings in other contexts. In any case, our results do show that new residential developments *can* improve access to groceries – in prices and varieties – to incumbent households.

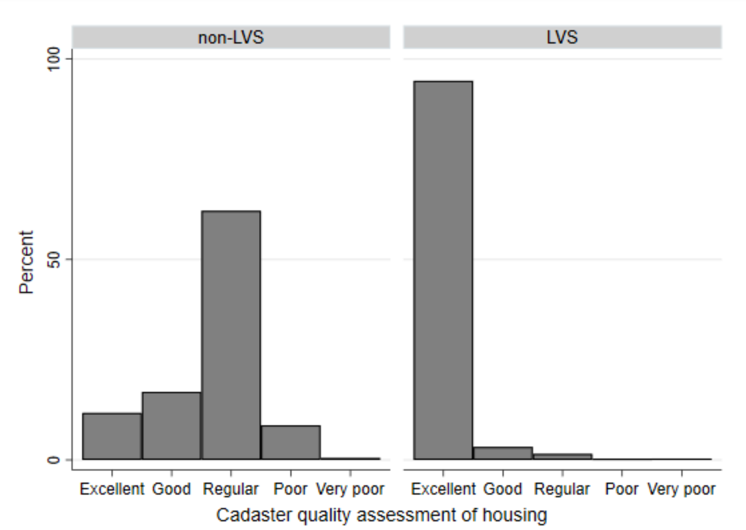
Online Appendices

A. Additional Figures and Tables

A.1. Quality of LVS units

FIGURE A.1

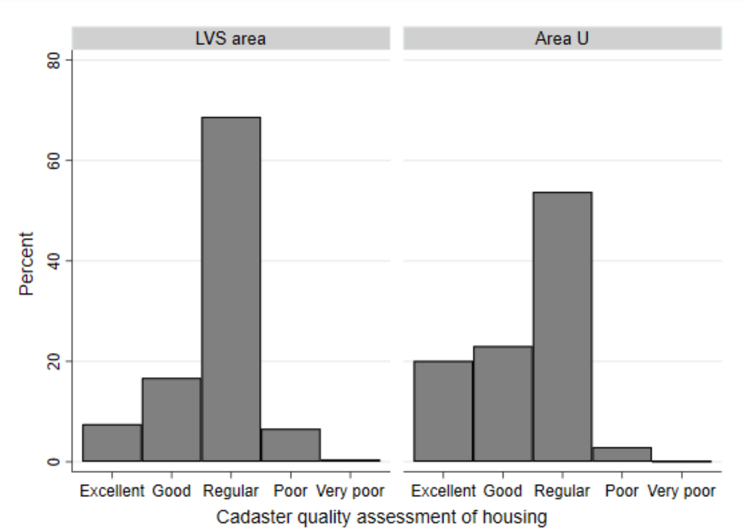
QUALITY OF LVS UNITS



Notes: The quality scale goes from 'Very poor' to 'Excellent'. Own calculations based on data from the Cadaster Agency (Municipal Property Registry). Left-panel displays the quality histogram for all housing units in Montevideo. Right-panel displays quality histogram for units on LVS developments.

FIGURE A.2

QUALITY OF HOUSING WITHIN TWO KM OF BORDER $S-U$



Notes: The quality scale goes from 'Very poor' to 'Excellent'. Own calculations based on data from the Cadaster Agency (Municipal Property Registry). Left-panel displays the quality histogram for all housing units in the policy area within 2km of the LVS border. Right-panel displays quality histogram for all units on the comparison region within 2km of the LVS border.

Figure A.3
Example of a LVS project

(a) Before

(b) After

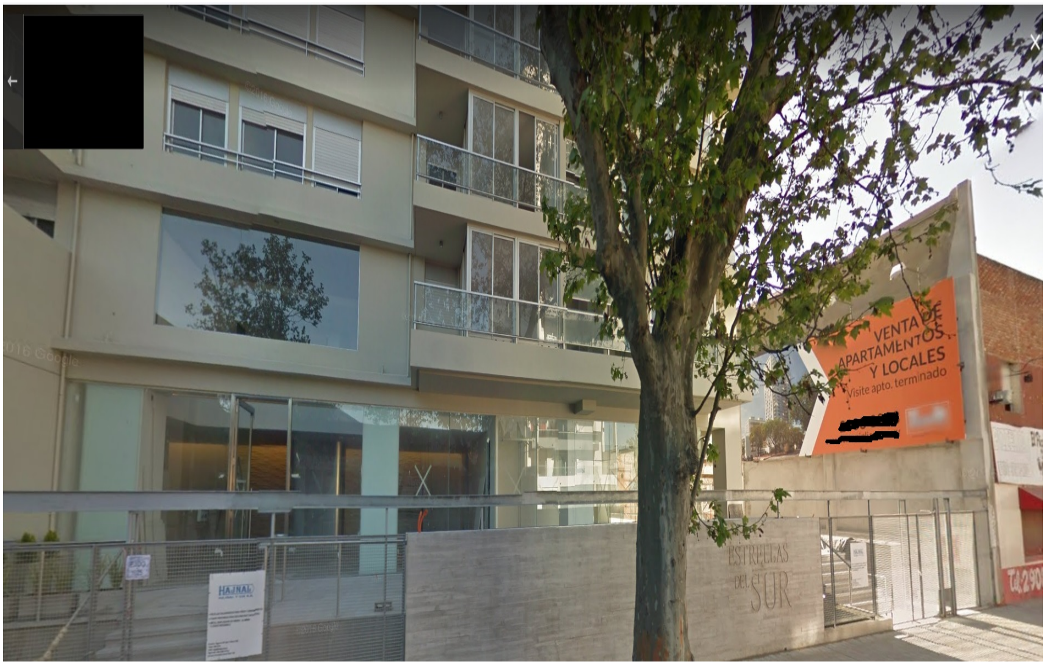
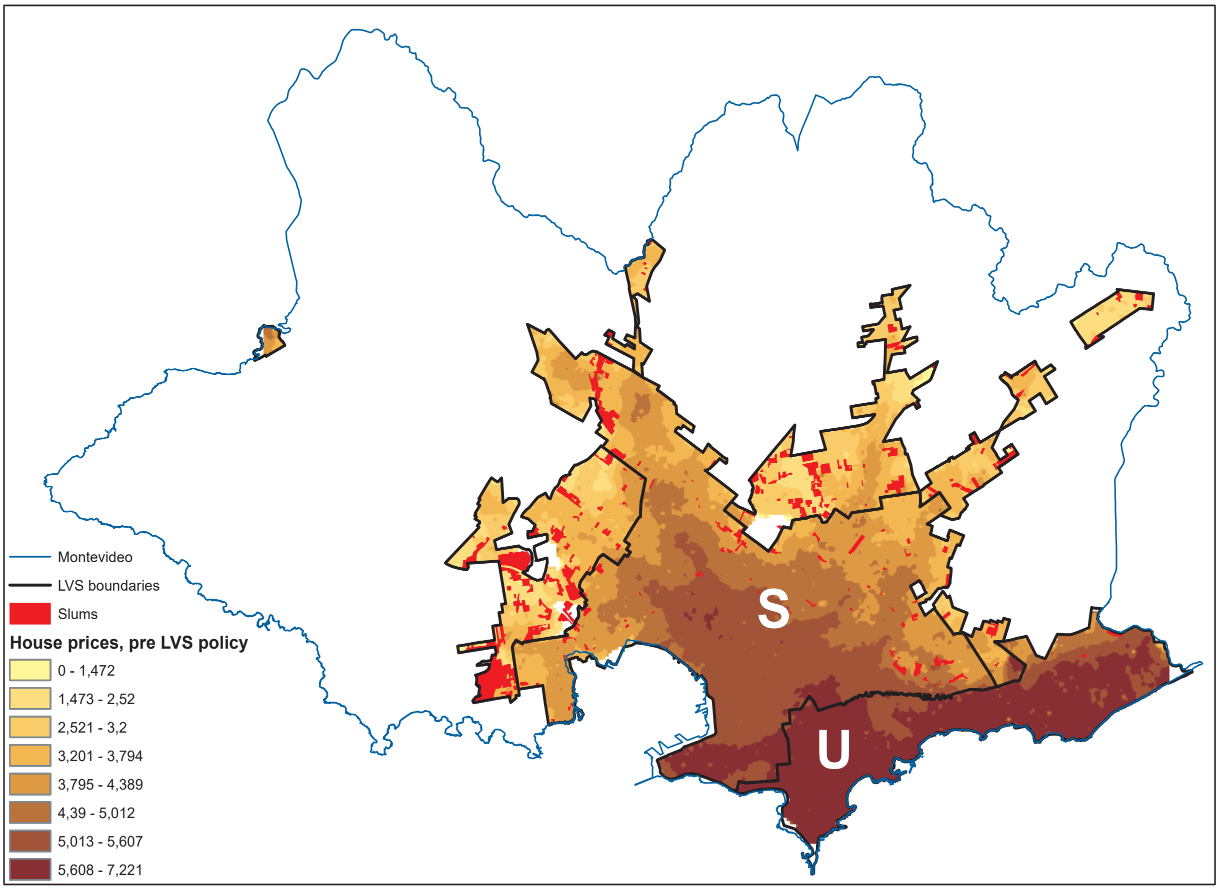


FIGURE A.4
MAP OF HOUSE PRICES (IN M^2, PRE LVS POLICY)



Notes: Map shows an inverse distance interpolation of the log of house prices (in m2) for the period 2004-2010, using grids of 100 $\times$ 100 metres and fixed search radius of 500 metres. Higher prices are represented with darker tones.

TABLE A.1
LIST OF PRODUCTS

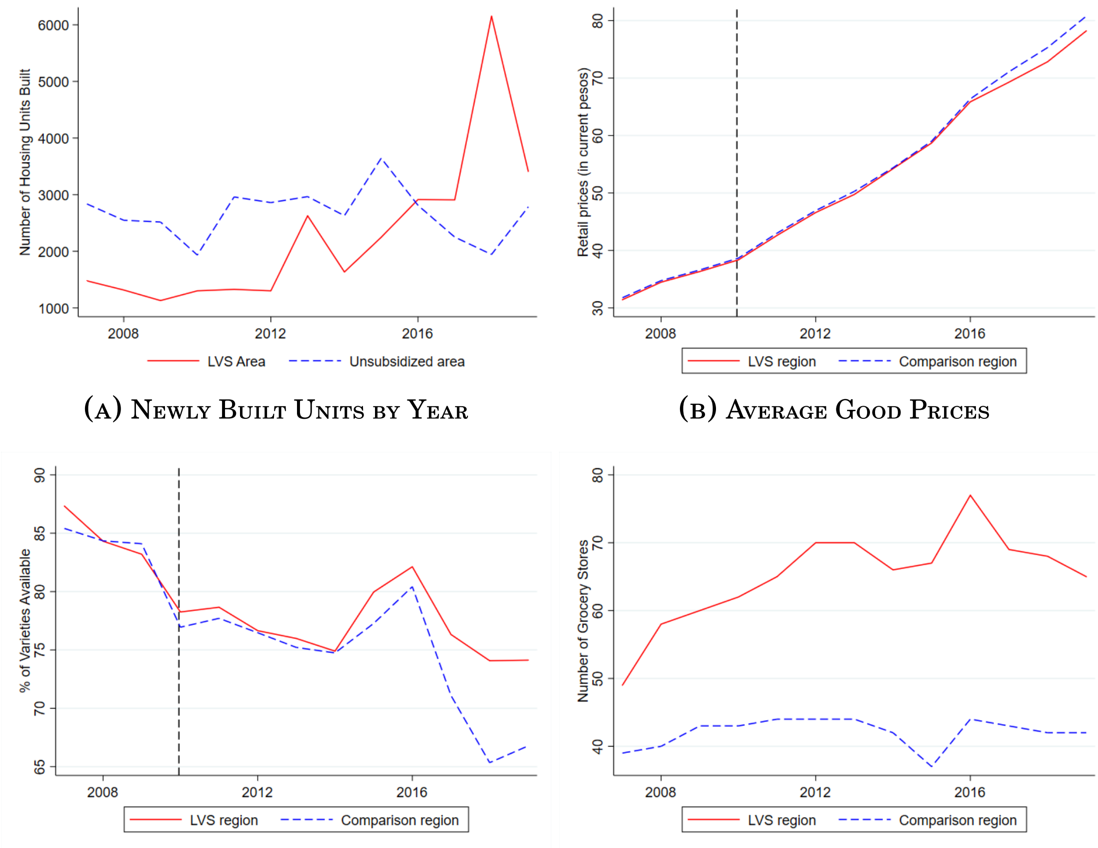
Product / Market	Brand	Specification*	UPC	% Share in CPI	Owner (/merger)	Sample Start (merge)
Beer	Patricia	0.96 L	7730452000435	0,36	FNC	2007/04
Beer	Pilsen	0.96 L	77302502	0,36	FNC	2007/04
Beer	Zillertal	1 L	7730452001319	0,36	FNC	2010/11
Wine	Faisán	1 L	7730540000187	0,80	Grupo Traversa	2007/04
Wine	Santa Teresa Clasico	1 L	7730135000035	0,80	Santa Teresa SA	2007/04
Wine	Tango	1 L	7730135000318	0,80	Almena	2007/04
Cola	Coca Cola	1.5 L	7730197232962	1,21	Coca Cola	2007/04
Cola	Nix	1.5 L	7730289000530	1,21	Milotur (CCU)	2007/04
Cola	Pepsi	1.5 L	7734284114087	1,21	Pepsi	2010/11
Cola	Coca Cola	2.25 L	7730197112967	1,21	Coca Cola	2010/11
Quince jelly	Los Nietitos	0.4 Kg	7730124020501	n/i	Los Nietitos	2009/01
Sparkling water	Matutina	2 L	7730922250070	0.81	Salus	2007/04
Sparkling water	Nativa	2 L	7730130000153	0.81	Milotur (CCU)	2007/04
Sparkling water	Salus	2.25 L	7730400000388	0.81	Salus	2007/04
Bread Loaf	Los Sorchantes	0.33 Kg	7730117000015	0,10	Bimbo / Los Sorchantes	2010/11
Bread Loaf	Bimbo	0.33 Kg	7730117001210	0,10	Bimbo	2010/11
Bread Loaf	Pan Catalán	0.33 Kg	7730230000336	0,10	Bimbo	2010/11
Brown eggs	Super Huevo	1/2 dozen	7730653000012	0,37	Super Huevo	2010/11
Brown eggs	El Jefe	1/2 dozen	7730637000045	0,37	El Jefe	2010/12
Brown eggs	Prodhin	1/2 dozen	7730239001211	0,37	Prodhin	2007/07
Butter	Calcar	0.2 Kg	7730901250176	0,22	Calcar	2007/04
Butter	Conaprole sin sal	0.2 Kg	77306197	0,22	Conaprole	2007/04
Butter	Kasdorf	0.2 Kg	7730105006357	0,22	Conaprole	2010/11
Cacao	Copacabana	0.5 Kg	7730109032154	0,07	Nestlé	2007/04
Cacao	Vascolet	0.5 Kg	7730109001686	0,07	Nestlé	2007/06
Coffee	Aguila	0.25 Kg	7730109012521	0,09	Nestlé	2007/04
Coffee	Chana	0.25 Kg	7730109012323	0,09	Nestlé	2007/04
Coffee	Saint	0.25 Kg	7730908360106	0,09	Saint Hnos	2010/11
Corn Oil	Delicia	0.9 L	7730132001196	n/i	Cousa	2010/11
Corn Oil	Río de la Plata	0.9 L	7730205040053	n/i	Soldo	2010/11
Corn Oil	Salad	0.9 L	7891080805738	n/i	Nidera	2010/11
Dulce de leche	Conaprole	1 Kg	7730105005091	0,13	Conaprole	2007/04
Dulce de leche	Los Nietitos	1 Kg	7730124384009	0,13	Los Nietitos	2007/04
Dulce de leche	Manjar	1 Kg	7730105005435	0,13	Manjar	2007/04
Flour (corn)	Gourmet	0.4 Kg	7730306000987	n/i	Deambrosi	2010/11
Flour (corn)	Presto Pronta Arcor	0.5 Kg	7790580660000	n/i	Arcor	2010/11
Flour (corn)	Puritas	0.45 Kg	7730354002322	n/i	Molino Puritas	2010/11
Flour 000 (wheat)	Cañuelas	1 Kg	7730376000085	0,16	Molino Cañuelas	2010/11
Flour 000 (wheat)	Cololó	1 Kg	7730213000506	0,16	Distribuidora San José	2010/11
Flour 0000 (wheat)	Cañuelas	1 Kg	7730376000061	0,16	Molino Cañuelas	2007/04
Flour 0000 (wheat)	Cololó	1 Kg	7730213000117	0,16	Distribuidora San José	2007/04
Flour 0000 (wheat)	Primor	1 Kg	7730133000105	0,16	Molino San José	2010/11
Grated cheese	Conaprole	0.08 Kg	7730105008832	0,14	Conaprole	2007/04
Grated cheese	Artesano	0.08 Kg	7730379000051	0,14	Artesano	2010/11
Grated cheese	Milky	0.08 Kg	7730153000185	0,14	Milky	2007/04
Deodorant	Axe Musk	0.105 Kg	7791293022130	0,27	Unilever	2010/11
Deodorant	Dove Original	0.113 Kg	7791293008141	0,27	Unilever	2010/11
Deodorant	Rexona Active Emotion	0.100 Kg	7791293004310	0,27	Unilever	2010/11
Hamburger	Burgy	0.2 Kg	7730138000575	n/i	Schneck	2010/11
Hamburger	Paty	0.2 Kg	7730901381146	n/i	Sadia Uruguay	2010/11
Hamburger	Schneck	0.2 Kg	7730138000599	n/i	Schneck	2010/11
Ice Cream	Conaprole	1 Kg	7730105912	0,24	Conaprole	2010/11
Ice Cream	Crufi	1 Kg	7730916580	0,24	Crufi	2010/11
Ice Cream	Gebetto	1 Kg	7730105980	0,24	Conaprole	2010/11
Margarine	Flor	0.2 Kg	7730132000571	n/i	Cousa	2010/11
Margarine	Doriana nueva	0.25 Kg	7805000300746	n/i	Unilever	2007/04
Margarine	Primor	0.25 Kg	7730132000533	n/i	Cousa	2007/04
Mayonnaise	Fanacoa	0.5 Kg	7790450086107	0,19	Unilever	2007/04
Mayonnaise	Hellmans	0.5 Kg	7794000401389	0,19	Unilever	2007/04
Mayonnaise	Uruguay	0.5 Kg	7730132000779	0,19	Unilever	2007/04
Noodles	Cololo	0.5 Kg	773021300	0,31	Distribuidora San José	2007/07
Noodles	Adria	0.5 Kg	773010330	0,31	La Nueva Cerro	2007/07
Noodles	Las Acacias	0.5 Kg	7730430000	0,31	Alimentos Las Acacias	2007/07

Table A.2
List of products (continued)

Product / Market	Brand	Specification*	UPC	% Share in CPI	Owner (/merger)	Sample Start (merge)
Peach jam	Dulciora	0.5 Kg	7790580508104	n/i	Arcor	2007/04
Peach jam	El Hogar	0.5 Kg	7730180086831	n/i	Lifibel SA	2010/11
Peach jam	Los Nietitos	0.5 Kg	7730124010304	n/i	Los Nietitos	2007/04
Peas	Campero	0.3 Kg	7730905130047	0,08	Regional Sur	2010/11
Peas	Cololó	0.3 Kg	7730213000018	0,08	Distribuidora San José	2010/11
Peas	Nidemar	0.3 Kg	7730332000975	0,08	Nidera	2010/11
Rice	Aruba tipo Patna	1 Kg	7730115170109	0,27	Saman	2007/04
Rice	Blue Patna	1 Kg	7730114000117	0,27	Coopar	2007/04
Rice	Green Chef	1 Kg	7730114400016	0,27	Coopar	2007/04
Rice	Pony	1 Kg	7730115020107	0,27	Saman	2010/11
Rice	Vidarroz	1 Kg	7730114000728	0,27	Coopar	2008/05
Rice	Saman Blanco	1 Kg	7730115040105	0,27	Saman	2010/11
Crackers	Famosa	0.14 Kg	7622300226480	0,25	Mondelez	2007/04
Crackers	Maestro Cubano	0.12 Kg	7730154000986	0,25	Bimbo	2007/04
Salt	Sek	0.5 Kg	77300607	0,08	Deambrosi	2007/04
Salt	Torrevieja	0.5 Kg	7730901390063	0,08	Torrevieja	2007/04
Salt	Urusal	0.5 Kg	7730214000062	0,08	UruSal	2007/04
Semolina pasta	Adria	0.5 Kg	77301030	0,31	La Nueva Cerro	2007/07
Semolina pasta	Las Acacias	0.5 Kg	7730430001	0,31	Alimentos Las Acacias	2007/07
Semolina pasta	Puritas	0.5 Kg	7730354001158	0,31	Molino Puritas	2010/11
Soybean oil	Condesa	0.9 L	7730132000434	0,09	Cousa	2008/05
Soybean oil	Río de la Plata	0.9 L	7730205067593	0,09	Soldo	2010/11
Soybean oil	Salad	0.9 L	7891080801693	0,09	Nidera	2010/11
Sugar	Azucarlito	1 Kg	7730251000018	0,24	Azucarlito	2007/04
Sugar	Bella Union	1 Kg	7730106005113	0,24	Bella Unión	2007/04
Sunflower oil	Optimo	0.9 L	7730132001165	0,29	Cousa	2007/04
Sunflower oil	Uruguay	0.9 L	7730132000441	0,29	Cousa	2007/04
Sunflower oil	Río de la Plata	0.9 L	7730205067661	0,29	Soldo	2010/11
Tea	Hornimans	Box (10 units)	7730261000046	0,08	José Aldao	2007/04
Tea	La Virginia	Box (10 units)	7790150572290	0,08	La Virginia	2007/04
Tea	President	Box (10 units)	7730220030527	0,08	Carrau	2010/11
Tomato paste	Conaprole	1 L	7730105015403	0,16	Conaprole	2007/04
Tomato paste	De Ley	1 L	7730306000604	0,16	Deambrosi	2007/04
Tomato paste	Gourmet	1 L	7730306000017	0,16	Deambrosi	2010/11
Yerba	Canarias	1 Kg	7730241003654	0,46	Canarias	2007/04
Yerba	Del Cebador	1 Kg	7730354000519	0,46	Molino Puritas	2007/06
Yerba	Baldo	1 Kg	7730241003920	0,46	Canarias	2010/11
Yogurt	Conaprole	0.5 Kg	7730105032820	0,13	Conaprole	2010/11
Yogurt	Parmalat (Skim)	0.5 Kg	7730112088520	0,13	Parmalat	2010/11
Yogurt	Calcar (Skim)	0.5 Kg	7730901250565	0,13	Calcar	2010/11
Bleach	Agua Jane	1 L	7731024003038	0,13	Electroquímica	2007/04
Bleach	Sello Rojo	1 L	7730494001001	0,13	Electroquímica	2007/04
Bleach	Solucion Cristal	1 L	7730377066028	0,13	Vessena SA	2007/04
Dishwashing detergent	Deterjane	1.25 L	7731024008118	0,11	Clorox Company	2007/04
Dishwashing detergent	Hurra Nevex Limon	1.25 L	7730165317424	0,11	Unilever	2007/04
Dishwashing detergent	Protergente	1.25 L	7730329024014	0,11	Electroquímica	2010/11
Laundry soap	Drive	0.8 Kg	779129078	0,35	Unilever	2007/04
Laundry soap	Nevex	0.8 Kg	779129020	0,35	Unilever	2007/04
Laundry soap	Skip, Paquete azul	0.8 Kg	77912902034	0,35	Unilever	2007/04
Laundry soap, in bar	Bull Dog	0.3 Kg (1 unit)	7791290677951	n/i	Unilever	2007/04
Laundry soap, in bar	Nevex	0.2 Kg (1 unit)	7791290677944	n/i	Unilever	2007/04
Laundry soap, in bar	Primor	0.2 Kg (1 unit)	7730205066	n/i	Soldo	2010/11
Shampoo	Fructis	0.35 L	78049600	0,31	Garnier	2007/04
Shampoo	Sedal	0.35 L	779129301	0,31	Unilever	2007/04
Shampoo	Suave	0.93 L	77912930083XX	0,31	Unilever	2007/04
Soap	Astral	0.125 Kg	7891024176771	0,14	Colgate	2010/11
Soap	Palmolive	0.125 Kg	7891024177XXX	0,14	Colgate	2007/04
Soap	Rexona	0.125 Kg	779129352XXXX	0,14	Unilever	2012/12
Toilet paper	Higienol Export	4 units (25 M each)	7730219001101	0,23	Ipusa	2007/04
Toilet paper	Elite	4 units (25 M each)	7790250021438	0,23	Ipusa	2010/11
Toilet paper	Sin Fin	4 units (25 M each)	7730219000494	0,23	Ipusa	2007/04
Toothpaste	Pico Jenner	0.09 Kg	7730366000170	0,17	Abarly / Colgate	2010/11
Toothpaste	Colgate Herbal	0.09 Kg	7891024133668	0,17	Colgate	2010/11
Toothpaste	Kolynos	0.09 Kg	7793100120121	0,17	Colgate	2010/11

Kg = kilograms; L = liters; M = meters. n/i - No information.

Figure A.5
Descriptives for Outcomes of Interest



(A) Newly Built Units by Year

(B) Average Good Prices

(C) Average Share of Varieties Available

(D) Number of Grocery Stores

Note: Descriptive patterns for all outcomes of interest, calculated separated by LVS and comparison regions within 2km of the LVS boundary. In **Panel A**, the vertical axis is the yearly count of newly built units in each area. In **Panel B**, the vertical axis is the average of current prices taken over goods and stores in our grocery price dataset. In **Panel C**, the vertical axis is the average store-level share of varieties available. In **Panel D**, the vertical axis is the number of stores present in a region. In all panels, the horizontal axis is the year in which the vertical axis variable is measures. Solid lines correspond to the path of the quantity of interest in the LVS or policy region. Dashed lines correspond to the path of the quantity of interest in the unsubsidized or comparison region.

Table A.3
Neighborhood Change & Access to Stores

	(1) Log(Stores within 1km)	(2) Log(Dist. Weighted Access)
Policy × Post	0.109* (0.056)	0.023 (0.015)
Obs.	852	854

Notes: Estimates obtained from a census tract panel covering years 2010 and 2019. In column 1, the outcome is the logarithm of the number of stores within 1km of a census tract. In column 2, the outcome is the logarithm of the inverse-distance weighted average of access to grocery stores. Standard errors are clustered at the level of $0.01^o \times 0.01^o$ grid cells. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.4
Price Effects in Continuing Stores

	(1)	(2)	(3)
Policy × Post	-0.019** (0.008)	-0.016** (0.007)	-0.021*** (0.008)
CPI Weights	No	Store	Global
Obs.	107374	107374	107374

Notes: Estimation based on product-store-time level observations. Sample restricted to continuing stores present in both 2010 and 2019. In all specifications the dependent variable is the logarithm of the product price. Estimate in column 1 is obtained without using product weights. Estimate in column 2 is obtained using store-level product weights. Estimate in column 3 is obtained using global product weights. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.5
Variety Effects in Continuing Stores

	(1)	(2)
Policy × Post	0.072** (0.035)	0.078** (0.035)
Sample of Goods	Consistent Sample	Full Sample
Obs.	170	170

Notes: Estimation based on store-year observations. Sample restricted to continuing stores present in both 2010 and 2019. The dependent variable is the share of available varieties offered in the store, measured in percentahe points Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.6

Price Differences between Stores in 2019

	(1)	(2)	(3)	(4)	(5)	(6)
New Entrant	0.054***	0.046***	0.043***	0.050***	0.035***	0.036***
	(0.009)	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)
Policy	-0.038***	-0.030***	-0.030***	-0.039***	-0.033***	-0.032***
	(0.007)	(0.006)	(0.006)	(0.009)	(0.007)	(0.007)
Policy × New Entrant				0.006	0.017*	0.010
				(0.014)	(0.010)	(0.011)
CPI Weights	No	Store	Global	No	Store	Global
Obs.	101343	101343	101343	101343	101343	101343

Notes: Estimation based on product-store-month level observations using data for 2019. In all specifications, the outcome is the logarithm of the product price. Estimates in columns 1 and 4 are obtained without using product weights. Estimates in columns 2 and 5 are obtained using store-level product weights based on CPI weights. Estimates in columns 3 and 6 are obtained using global product weights based on CPI weights. Standard errors clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.7

Variety Differences between Stores in 2019

	(1)	(2)
New Entrant	-0.034	0.010
	(0.025)	(0.041)
Policy	0.063*	0.076*
	(0.033)	(0.040)
Policy × New Entrant		-0.067
		(0.051)
Obs.	107	107

Notes: Estimation based on store level observations using data for 2019. The dependent variable is the share of available varieties offered in the store, measured in percentage points. Set of available varieties corresponds to the full sample of goods. Column 2 includes the interaction term as indicated. Standard errors clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.8

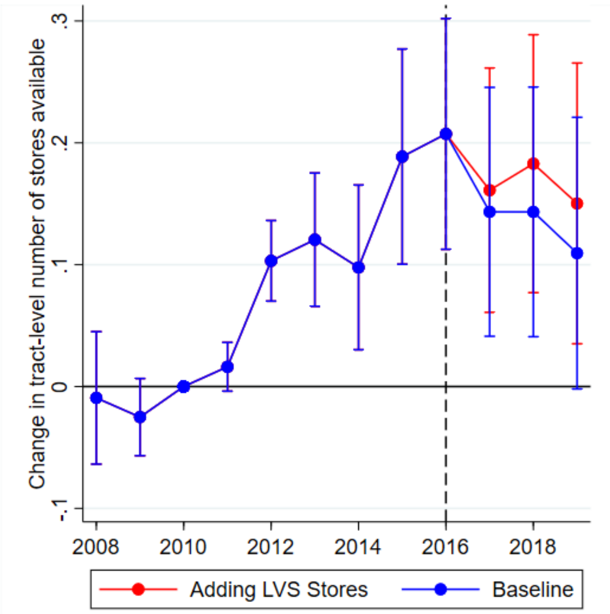
Variety Effects – Controlling for Addition of Commercial Space

	(1)	(2)
Policy × Post	0.095***	0.104***
	(0.035)	(0.035)
Commercial LVS × Post	-0.061*	-0.067*
	(0.037)	(0.037)
Sample of Goods	Consistent Sample	Full Sample
Obs.	212	212

Notes: Estimates obtained from store-level specifications. The outcome variable in both specifications is the share of available varieties at the store level, measured in percentage points. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

FIGURE A.6

ACCESS TO STORES INCORPORATING LVS PROJECT STORES



Notes: Event-study graphs for changes in access to stores with and without considering the 4 grocery stores identified in LVS projects, open before 2019 and not included in the DGC sample. Access to stores measured as the (logarithm) number of stores within 1km of census tract as the dependent variable. Round markers indicate estimated coefficients from a census tract level regression of grocery shop access on interaction terms between $Policy_c$ and year dummies featuring census tracts and time effects (see equation 4). Vertical segments correspond to 95% confidence bands. The dashed line corresponds to 2016, the year after which a large share of LVS units were sold in the housing market.

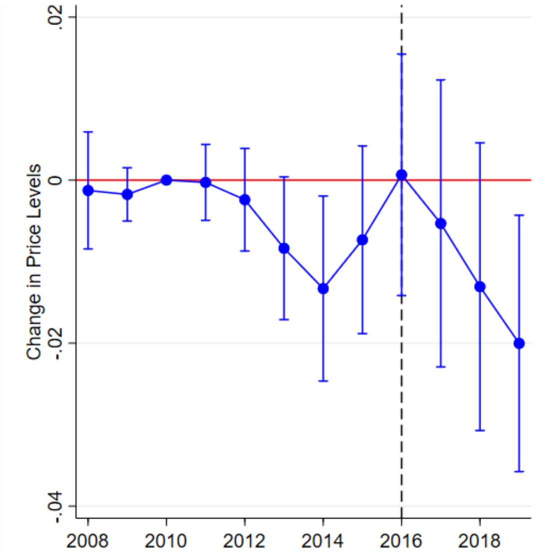
TABLE A.9

ROBUSTNESS CHECKS - PRODUCT VARIETIES

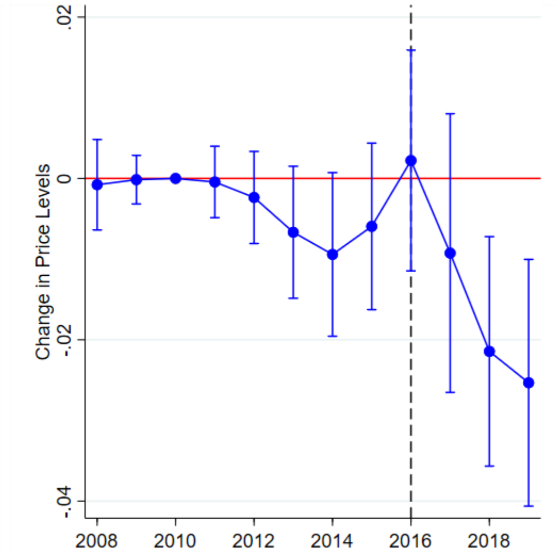
	Baseline Year: 2008	Baseline Year: 2012
A. Alternative Baseline Year		
Policy × Post	6.525**	6.992**
	(3.183)	(3.463)
Obs.	205	221
	1.5km Band	2.5km Band
B. Bandwidth Around Boundary		
Policy × Post	7.654**	6.888**
	(3.367)	(3.059)
Obs.	176	228

Notes: Estimates obtained from store-level specifications. The outcome variable in both specifications is the share of available varieties at the store level, measured in percentage points. Panel A represents estimates obtained using 2008 as the baseline year (column 1) and 2012 as the baseline year (column 2). Panel B presents results using different bands around the LVS border to define the sample. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

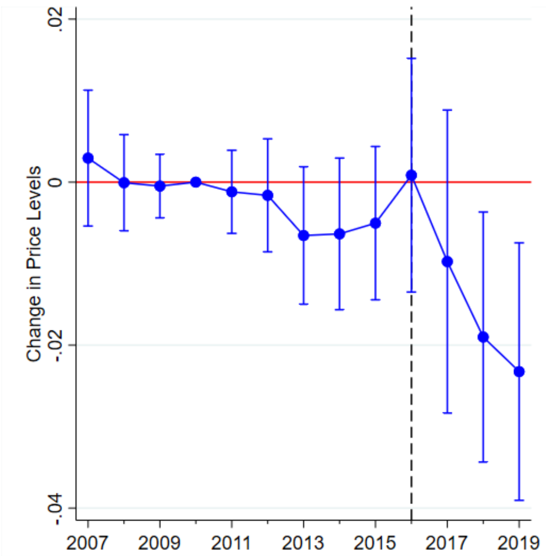
Figure A.7
Event-Study Graph: Prices



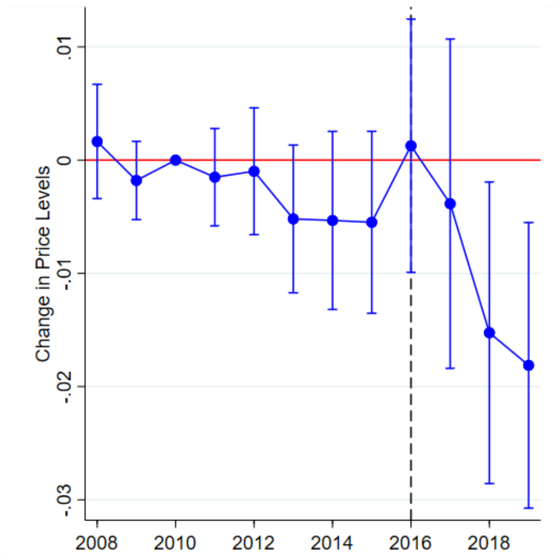
(A) Using store-level product weights



(B) Using global product weights



(C) Including 2007



(D) Product-brand fixed effects

Note: All panels represent event-study coefficient sequences obtained using specification 2. In all cases, the dependent variable is the logarithm of product prices. **Panel A** represents estimates obtained using store-level product weights. **Panel B** represents estimates obtained using store-level product weights. **Panel C** represents estimates obtained after extending the sample from 2007 (incomplete year). **Panel D** represents estimates obtained in a specification featuring product-brand specific time effects instead of product group-time effects. Round markers indicate estimates for the sequence of coefficients in equation 2. Vertical bars correspond to 95% confidence intervals. Effects are relative to 2010, the omitted year. Vertical segments correspond to 95% confidence bands. While the LVS program began in 2011, dashed vertical lines correspond to 2016, the year after which a large share of LVS units were sold in the housing market.

TABLE A.10

ROBUSTNESS CHECKS - ENTRY

	Baseline Year: 2008		Baseline Year: 2012	
	<1km	1/d	<1km	1/d
A. Alternative Baseline Year				
Policy × Post	0.119*	0.029	0.006	-0.011
	(0.065)	(0.017)	(0.054)	(0.015)
Obs.	852	854	852	854
	1.5km Band		2.5km Band	
	<1km	1/d	<1km	1/d
B. Bandwidth Around Boundary				
Policy × Post	0.116**	0.027*	0.105*	0.023
	(0.053)	(0.014)	(0.056)	(0.016)
Obs.	690	692	934	938

Notes: Estimates obtained from a census-tract level panel. The outcome is either the logarithm of the number of stores within 1km of a census tract or the logarithm of the inverse-distance weighted average of access to grocery stores, as indicated in each column. Panel A represents estimates obtained using 2008 (columns 1 and 2) or 2012 (columns 3 and 4) as the baseline year. Panel B presents results using different bands around the LVS border to define the sample. Standard errors are clustered at the level of $0.01^o \times 0.01^o$ grid cells. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

TABLE A.11

PRICE EFFECTS – HETEROGENEITY BY PRODUCT SEGMENT

	High-price brand		Low-price brand	
Policy × Post	-0.023***	-0.021***	-0.023***	-0.021**
	(0.007)	(0.006)	(0.008)	(0.008)
CPI Weights	N	Y	N	Y
Obs.	74699	74699	106447	106447

Notes: Estimates from product-store-month regressions using years 2010 and 2019. The outcome variable in all specifications is the logarithm of the price of a good. Sub-samples of high-price (top priced) and low-price (other) goods for each product category as described in the main text. CPI weights in columns 2 and 4 correspond to product-store weights. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

TABLE A.12

PRICE EFFECTS – INCLUDING PHARMACIES

	(1)	(2)	(3)
Policy × Post	-0.029***	-0.028***	-0.036***
	(0.008)	(0.008)	(0.008)
CPI Weights	No	Store	Global
Obs.	147312	147312	147312

Notes: Estimates from product-store-month regressions using years 2010 and 2019. Sample expansed to include prices of products sold by pharmacy chains featured in the DGC dataset. The dependent variable is the logarithm of product price and we use the consistent sample of goods in all specifications. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Table A.13

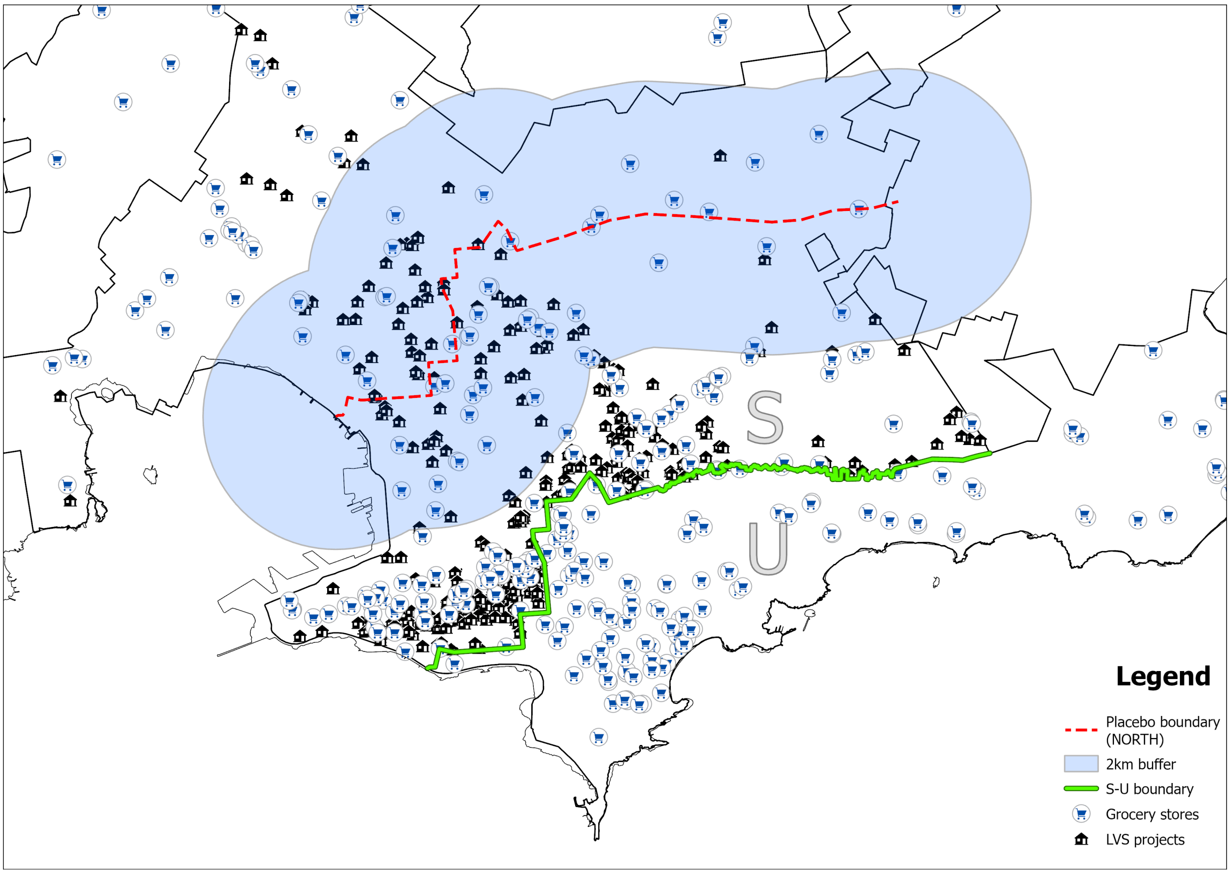
Variety Effects – Including Pharmacies

	(1)	(2)
Policy × Post	0.117***	0.116***
	(0.037)	(0.037)
Sample of Goods	Consistent Sample	Full Sample
Obs.	277	277

Notes: Estimates based on store-year regressions using years 2010 and 2019. Sample expanded to include pharmacies featured in the original DGC dataset. The outcome variable in both columns is the share of available varieties at the store level, measured in percentage points. In column 1 the outcome is built using the consistent sample of good. In column 2 the outcome is built all identifiable goods in the DGC database. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

Figure A.8

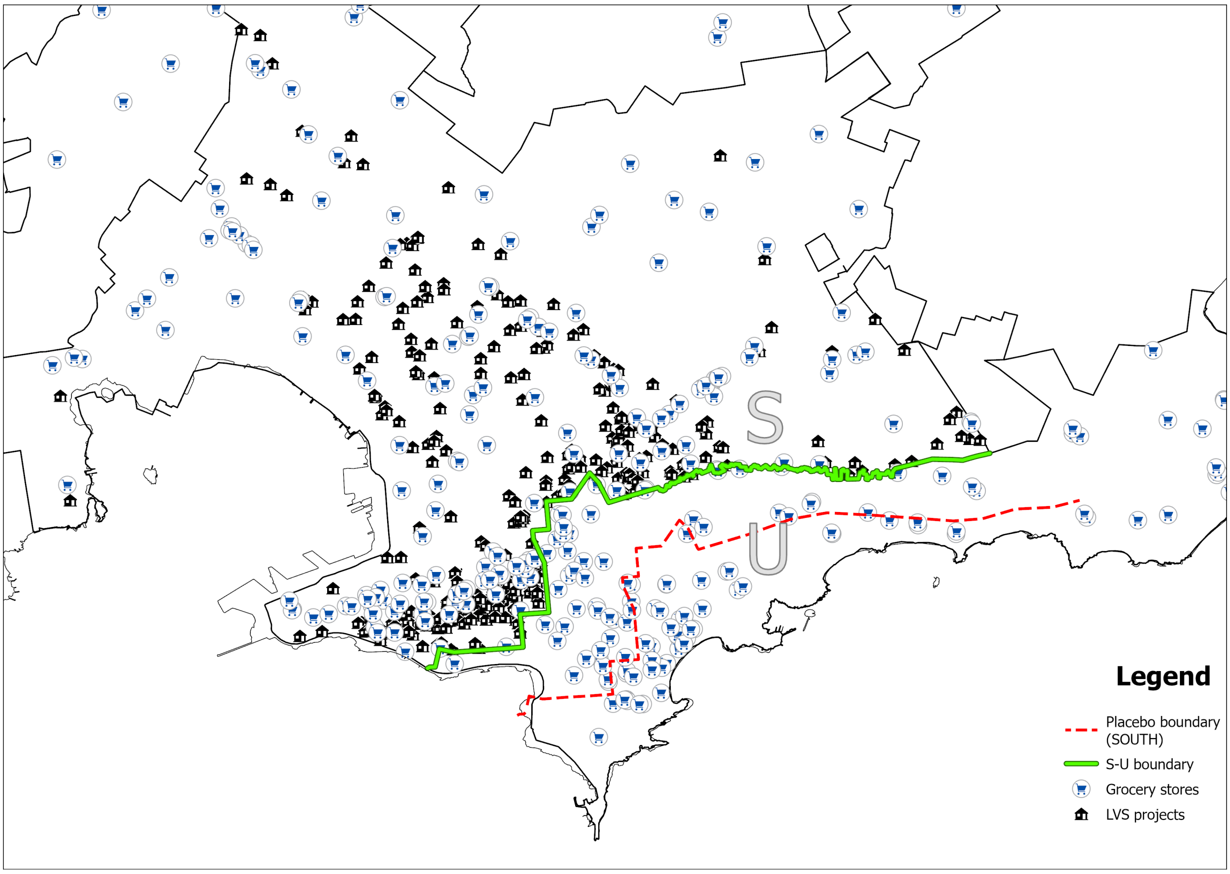
Placebo exercise NORTH



Notes: The placebo boundary resulted from shifting the LVS border ($S-U$ border if Figure 1) to cross the centroid of the LVS region.

FIGURE A.9

PLACEBO EXERCISE SOUTH



Notes: Illustration of the placebo boundary resulting from shifting the LVS border ($S-U$ border) to the mid-point of the unsubsidized area.

TABLE A.14

PLACEBO - VARIETIES

	(1) Varieties Share (%)	(2) Varieties Share (%)
Post × Placebo	-4.563	3.386
	(4.498)	(4.535)
Placebo	South	North
Obs.	1093	769

Notes: Estimates based on store-year regressions using years 2010 and 2019. The outcome variable in both columns is the share of available varieties at the store level, measured in percentage points. Column 1 corresponds to estimates obtained when using the sample resulting from shifting the LVS border into the LVS region. Column 2 corresponds to estimates obtained using the sample resulting from shifting the LVS border into the unsubsidized area. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

B. Instrumental Variable Estimates

In this appendix, we present the results obtained when using an instrumental variable approach to estimate the effect of measures of new development on our outcomes of interest. This strategy consists of using the policy as an instrument for new development – i.e., the first-stage – to estimate the elasticity of new development with respect to our three outcomes of interest (retail prices, store varieties, and store access) – i.e., the second-stage. Table B.1 shows the first stage estimates – the effect of the policy on new development – for different levels of aggregation of our dataset on stores and our census tract panel. Estimates using data for 2010 (the year before the introduction of the LVS) and 2019 (the final year in our sample, when a substantial amount of LVS units have been incorporated into the housing market). Panel A shows first-stage estimates when using monthly-product data at the store level. Panel B shows the first-stage results for yearly store-level data. Panel C presents results for yearly tract-level data. We further describe results from each panel as well as the second-stage estimates for each of our three outcomes in the following subsections.

TABLE B.1
EFFECT OF THE LVS POLICY ON NEW RESIDENTIAL DEVELOPMENT

	(1) Log(New Units)	(2) Log(New Area)
A. Product × month × store level		
Post × Treat	0.532***	0.638***
	(0.131)	(0.139)
F-stat	16	22
Obs.	131493	131493
B. Store × Year level		
Post × Treat	0.573***	0.695***
	(0.132)	(0.145)
F-stat	18	22
Obs.	212	212
C. Census Tract × Year level		
Policy × Post	0.728***	0.846***
	(0.130)	(0.119)
F-stat	32	50
Obs.	738	738

Notes: Panel A presents estimates from product-store-month regressions. Panel B presents estimates from store-year regressions. Panel C presents estimates from a census-tract year panel. In all cases, estimates are obtained using data for 2010 and 2019. In column 1, the outcome is the logarithm of the number of new units built within 1km of a store (panels A and B) or a census tract (panel C). In column 2, the outcome is the logarithm of the floor area of new units built within 1km of a store (panels A and B) or a census tract (panel C). F-statistics for a significance test of the interaction term reported in the foot of each panel. In Panels A and B, standard errors are clustered at the store level. In panel C standard errors are clustered at the level of $0.01^o \times 0.01^o$ grid cells. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

B.1. The Elasticity of Retail Prices to New Development

We first focus on estimating the elasticity of prices to new development. To do so, we use the spatial and time variation in eligibility for the LVS tax exemption as an instrument for housing construction activity. New construction activity New Area$_{st}$ is measured as the sum of the floor area (in m^2) of new units within 1km of supermarket s.[1] The variable is constructed using the accumulated stock of new units within six years of t (i.e., between $t-6$ and t).[2] As discussed in the text, we use the accumulated change over this period in an effort to measure changes to the density and vintage of the local housing *stock* rather than simply the *flow* change in construction in one given year. This variable measures the exposure of each supermarket s to new residential construction and, therefore, to changes in local demand for its goods. We estimate the effect of New Area on local retail prices by estimating the parameter of interest η_P via two-stage least squares (2SLS) where the two stages are given by:

$$Log(\text{New Area}_{ist}) = \pi Policy_s \times post_t + \eta Policy_s + \omega_{it} + u_{ist} \tag{B.1}$$

$$Log(P_{ist}) = \eta_P Log(\text{New Area}_{st}) + \delta_{it} + \alpha Policy_s + \epsilon_{ist} \tag{B.2}$$

where equation B.1 is the first-stage and B.2 is the second-stage. Most variables in these equations are defined as in the main text except for ω_{it}, representing the product-time effects in the first stage. As with our reduced-form estimates, estimation is carried out using only the sample of stores within two kilometers of the LVS boundary and data for 2010 and 2019. Our first-stage estimates reported in panel A of Table B.1 indicate supermarkets in the policy region experienced an around 60% increase in the area of new stock within 1km of their location relative to stores located in the comparison region. The instrument is reasonably strong, with an F-statistic of 16 and 22 when measuring new development using units and floor area, respectively. Instrumental variable estimates of the elasticity of grocery prices to new residential development are reported in columns 1 to 3 of Table B.2. Estimates in columns 2 and 3 were obtained using store-level and global CPI based weights. The estimated elasticity of retail prices with respect to new housing area ranges from -3% to -3.9%.

B.2. Elasticity of Product Variety to New Development

Here we focus on estimating the elasticity of new development on the varieties available to consumers locally. We use the same empirical strategy to estimate the elasticity with respect to prices, i.e., we rely on exogenous variation induced by the shift in construction activity within the city induced by the LVS. As explained in the main text, we measure varieties at the supermarket level - Variety share$_{st}$ -, by calculating the percentage of reported products included in our price database offered at supermarket s and month t. We estimate the effect

[1]We can also measure new development using the *number* of new units built around each store. We use this alternative as a robustness check, and the estimated elasticities remain largely unchanged. Results are available upon request.

[2]We chose six years because the first new units built under the aegis of the LVS were sold in 2013, six years before 2019.

TABLE B.2

IV ESTIMATES: PRICE ELASTICITY OF NEW DEVELOPMENT

	(1)	(2)	(3)
Log(New Area)	-0.036**	-0.030**	-0.039**
	(0.016)	(0.015)	(0.016)
CPI Weights	No	Store	Global
1st F-stat	21	21	21
Obs.	131493	131493	131493

Notes: Instrumental variable estimates from product-store-month specifications. In all columns the outcome variable is the logarithm of the product price. Estimate in column 1 obtained without using product weights. Estimate in column 2 obtained using store-level product weights. Estimate in column 3 obtained using global product weights based. Standard errors are clustered at the store level. First-stage F-statistic indicated in the table foot. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

of New Area$_{st}$ on available varieties by estimating the parameter of interest η_V via two-stage least squares (2SLS) where the two stages are given by:

$$Log(\text{New Area}_{st}) = \pi Policy_s \times post_t + \eta Policy_s + u_{st} \tag{B.3}$$

$$\text{Variety share}_{st} = \eta_V Log(\text{New Area}_{st}) + \delta_t + \alpha Policy_s + \epsilon_{st} \tag{B.4}$$

where equation B.3 is the first-stage and B.4 is the second-stage. The estimation is carried out using only the sample of stores within 2 kilometers of the LVS boundary and data for 2010 and 2019. Our first-stage estimates reported in panel B of Table B.1 indicate supermarkets in the policy region experienced a sharp increase in the area of new stock within 1km of their location relative to stores located in the comparison region. These estimates correspond to those illustrated in Figure 3 of the main text. The instrument is reasonably strong, with an F-statistic of 18 and 22 when measuring new development using units and floor area, respectively. Table B.3 reports IV estimates of the elasticity of the share of varieties available to new residential development. Estimates in columns 1 and 2 were obtained using the consistent sample of goods and the full sample of goods, respectively.[3] Results indicate that a one percent increase in newly built residential area within 1km of a store increases varieties available by around 0.10 percent (note that the outcome is measured in percentage points).

B.3. Effects on Store Access

Finally, we report IV estimates of the effect of new residential development on grocery store access measured at the census tract level. New residential development is measured as the logarithm of the floor area of newly built stock in census tract c in the six years before

[3]As explained in the main text, the *consistent sample of goods* includes the 73 unique grocery products consistently present from 2007 to 2019, and the *full sample of goods* includes the 127 unique grocery products even those included in the price database in 2010.

Table B.3

IV Estimates: Product Variety & New Development

	(1)	(2)
Log(New Area)	9.406*	10.299*
	(5.242)	(5.414)
First-stage F-stat	22	22
Sample	Consistent Sample	Full Sample
Obs.	212	212

Notes: Instrumental variable estimates from store-year specifications. The outcome variable in both columns is the share of available varieties at the store level, measured in percentage points. In column 1 the outcome is built using the consistent sample of good. In column 2 the outcome is built all identifiable goods in the DGC database. First-stage F-statistics indicated in the table foot. Standard errors are clustered at the store level. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

year t.[4] We consider two tract-level outcomes that measure grocery access. The first is defined as the log of the number of stores within 1km. The second is defined as the log of the inverse distance weighted access to grocery stores. Then, we estimate the effect of New Area$_{ct}$ on these two measures of grocery access - Grocer Access$_{ct}$ - by estimating the parameter of interest η_A via two-stage least squares (2SLS) where the two stages are given by:

$$Log(\text{New Area}_{ct}) = \pi Policy_c \times post_t + \eta Policy_c + u_{ct} \tag{B.5}$$

$$\text{Grocer Access}_{ct} = \eta_A Log(\text{New Area}_{ct}) + \delta_t + \alpha Policy_c + \epsilon_{ct} \tag{B.6}$$

where equation B.5 is the first-stage and B.6 is the second-stage. The estimation is carried out using census tracts within two kilometers of the LVS boundary and data for 2010 and 2019. Our first-stage estimates reported in panel C of Table B.1 indicate supermarkets in the policy region experienced a substantial increase in new developments in tract located in the LVS area relative to tract in the comparison region. The instrument is reasonably strong, with an F-statistic of 32 and 50 when measuring new development using units and floor area, respectively. Table B.4 reports IV estimates of the elasticity of grocery access to new residential development.[5] Estimates in columns 1 and 2 were obtained using the number of stores within 1km, and inverse distance weighted access, respectively. Similar to our reduced-form estimates, results indicate positive but somewhat imprecisely estimated effects of new development on store access. They do allow us to confidently reject with some confidence substantial negative effects of new development on store access.

[4] Census tracts are relatively small geographies, with a total of 969 areas in the Montevideo, and over 450 areas within 2km of the LVS region boundary.

[5] In order to accommodate for the role of spatial dependence when conducting inference, we cluster at the level of $0.01^o \times 0.01^o$ cells. This leaves us with 60 spatial clusters in the sample of census tracts within 2km of the LVS boundary.

Table B.4

IV Estimates: Entry & New Development

	(1) Log(Stores within 1km)	(2) Log(Dist. Weighted Access)
Log(New Area)	0.123*	0.029
	(0.065)	(0.018)
1st Stage F-stat	51	51
Obs.	736	738

Notes: Instrumental variable Estimates obtained from a census tract panel covering years 2010 and 2019. In column 1, the outcome is the logarithm of the number of stores within 1km of a census tract. In column 2, the outcome is the logarithm of the inverse-distance weighted average of access to grocery stores. First-stage F-statistics reported in the table foot. Standard errors are clustered at the level of $0.01^o \times 0.01^o$ grid cells. *, **, and *** represent 10%, 5%, and 1% significance levels, respectively.

C. Theoretical Appendix

The Lagrangian associated to the consumer problem is given by

$$\mathcal{L} = q_0 + \alpha \sum_j q_i - \frac{1}{2}\gamma \sum_j (q_i)^2 - \frac{1}{2}\eta \left(\sum_j q_i\right)^2 + \lambda \left[y - q_0 - \sum_j p_j q_j\right]$$

From the FOCs with respect to q_0 we obtain $\lambda = 1$, while from the FOCs for variety j we obtain $\frac{\partial \mathcal{L}}{\partial q_i} = 0 = \alpha - \gamma q_i - \eta \sum_j q_i - \lambda p_i \Longrightarrow p_i = \alpha - \gamma q_i - \eta Q$.

The first order conditions for the firms' problem are given by

$$\alpha - c - \frac{\gamma q_j^m}{L} - \frac{\gamma \sum_{k=1}^{M} q_j^k}{L} - \eta \left(\frac{q_j^m + \sum_{k=1}^{M} \sum_{i=1}^{N} q_i^k}{L}\right) = 0 \tag{B.1}$$

C.1. *Proof of Proposition 1*

In the final stage - when choosing quantities for a fixed N - the monopolist's problem becomes:

$$\max_{\{q_j\}_{j=1}^N} \sum_{j=1}^{N} q_j \left[\alpha - c - \frac{\gamma q_j}{L} - \eta \frac{\sum_{i=1}^{N} q_i}{L}\right]$$

Taking first order conditions for all varieties we obtain:

$$L(\alpha - c) - 2\gamma q_j - \eta q_j - \eta \sum_{i=1}^{N} q_i = 0$$

Given that, for an optimal choice of N, no q_j is equal to zero, these FOCs hold for all js. We can therefore solve for a generic j and obtain that in the symmetric equilibrium:

$$q^* = \frac{L(\alpha - c)}{2\gamma + \eta(1+N)} \qquad p^* = \frac{\alpha(\gamma + \eta) + c(\gamma + \eta N)}{2\gamma + \eta(1+N)}$$

Substituting these in the equation for profits in the varieties choice stage we obtain profits as a function of the number of varieties.

$$\pi(N) = \frac{L(\alpha - c)^2(\gamma + \eta)N}{(2\gamma + \eta(1+N))^2} - F_N N \tag{B.2}$$

To save on notation, we can re-write this expression as $\pi(N) = f(N) - F_N N$, where $f(N)$ is the first term in the right hand side of B.2. It is worth noting that the derivative of $f(N)$ is strictly decreasing in N, so the problem is concave. Therefore, it suffices to define the profit maximizing number of varieties N^* as the N that satisfies the condition $\pi(N) > \max\{\pi(N+1), \pi(N-1)\}$.

We now show that the number of varieties increases with market size L. Formally, this means that with L_1 and L_2 such that $L_2 > L_1$ – then $N^*(L_2) > N^*(L_1)$ where $N^*(.)$ is the optimal N for a given value of L. Define $\Delta(N) \equiv f(N) - f(N-1)$. Note that, because $f(.)$ is continuous and its derivative is decreasing in N, the function $\Delta(N)$ is also decreasing in N.

Given these conditions we can write the following system of inequalities:

$$L_2[\Delta(N^*(L_2))] - F_N > 0 \tag{B.3}$$
$$L_1[\Delta(N^*(L_1))] - F_N > 0 \tag{B.4}$$
$$L_1 << L_2 \tag{B.5}$$

Where the first and second conditions derive from the definition of $N^*(L)$ and the third is true by construction. Proceed by contradiction. Suppose that $N^*(L_1) = N^*(L_2)$. If this were the case, then – for low enough L_1 –either B.3 or B.4 need to be false, as the lower value of L_1 reduces the value of the positive component of B.4. Suppose instead that $N^*(L_1) > N^*(L_2)$. The fact that $\Delta(N^*(L_1))$ means that this would result again in a contradiction as the reduction from L_2 to L_1 is coupled with a reduction in $\Delta(N^*(L_1))$. Therefore, it has to be true that $N^*(L2) \geq N^*(L1)$ for $L_2 > L_1$.

It remains to show that this increase in varieties results in a reduction in prices. This is straightforward to see in the expression on p^* above, which is decreasing in N for the parameter restrictions outlined in the main text.

■

C.2. ***Proof of Proposition 2***

In the final stage, when choosing quantities, the first order conditions of firm m's problem can be written as:

$$L(\alpha - c) - \gamma q_j^m - \gamma \sum_{k=1}^{M} q_j^k - \eta \left(q_j^m + \sum_{k=1}^{M} \sum_{i=1}^{N} q_i^k \right) = 0$$

Define $Q_j \equiv \sum_{k=1}^{M} q_j^k$ and $Q \equiv \sum_{k=1}^{M} \sum_{i=1}^{N} q_i^k$. If we add the first-order conditions across firms first and then across varieties (js) we obtain:

$$M\left(L(\alpha - c) - \gamma Q_j - \eta Q\right) = (\gamma + \eta) Q_j$$
$$NM\left(L(\alpha - c) - \eta Q\right) = (\gamma + \eta + \gamma M) Q$$

Using these two expressions we can solve for Q, Q_j and q_j^m. Moreover, replacing the equilibrium value of q_j^m on demand we can obtain equilibrium prices. The resulting equilibrium expressions for quantities and prices are:

$$q^* = \frac{L(\alpha - c)}{\gamma + \eta + \gamma M + \eta NM} \qquad p^* = \frac{\alpha(\gamma + \eta) + c(\gamma M + \eta NM)}{\gamma + \eta + \gamma M + \eta NM}$$

Substituting these expressions in the firm's pay-off function we can obtain the expression for profits net of entry costs:

$$\Pi(M) = \frac{NL(\alpha - c)^2(\gamma + \eta)}{\gamma + \eta + \gamma M + \eta NM} - F - F_N N \tag{B.6}$$

The equilibrium number of firms is given by $M^* : \Pi(M^*) > 0, \Pi(M^* + 1) < 0$. Note that, an increase in L (keeping N fixed) can have two outcomes: either M^* stays the same or it increases. Re-writing $\Pi(M^*(L)) = Lg(M) - F - F_N N$ we know that:

$$L_2 g(M^*(L_2) + 1) < F + F_N N$$
$$L_1 g(M^*(L_1) + 1) < F + F_N N$$

Suppose $L_2 >> L_1$. In that case, we must have that $M^*(L_2) > M^*(L_1)$, otherwise (for sufficiently large gap between L_2 and L_1, either the first or the second inequality will not be satisfied. This proves that, for a fixed number of varieties, a large enough change in market scale L will lead to a larger number of firms in equilibrium. It is straightforward to see that this will result in a lower value of p^*, as long as $\alpha > c$.

■

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