A Framework to Evaluate Difference-in-Differences Estimates of Placed-Based Policies

Guillermo Alves* William H. Burton† Sebastian Fleitas‡

Preliminary and incomplete, please do not share

January 2023

Abstract

We propose a framework to evaluate place-based policies when they are large enough to induce substantial relocation of agents between treated and untreated areas. We show that, in such contexts, reduced-form estimates obtained by comparing only the most similar control and treated areas may lead to serious overstatements of the efficiency costs of the policy. This is because consumers substitute more easily between similar areas. We illustrate our argument by studying a large tax break for housing development in lagging areas of Montevideo, the capital of Uruguay. First, we obtain a series of difference-in-differences estimates of the effect of the policy on housing prices and show that they differ widely depending on the degree of heterogeneity between subsidized and unsubsidized areas. Consistent with our conceptual framework, prices fall substantially when comparing heterogeneous areas, and very little or not at all when comparing similar areas. Second, we estimate a structural model of supply and demand for neighborhoods that rationalizes those different estimates and allows us to obtain welfare results. Preliminary results indicate that reduced-form difference-in-differences estimates understate the share of the subsidy that reaches consumers by around 20 percentage points.

Keywords: Regulation, Place-Based Policies, Supply-Side Incentives, Spillovers
JEL Codes: R31, R13, H22, L78

*CAF Development Bank of Latin America.
†KU Leuven and FWO.
‡KU Leuven and CEPR.

1 Introduction

Place-based interventions exist in a variety of areas, ranging from industrial policies to urban revitalization programs, and they have become more popular in the last few decades (Kline and Moretti, 2014b). Because these policies target places rather than individuals, they can lead to large inefficiencies if they cause economic agents to relocate from untreated to treated areas (E. L. Glaeser and Gottlieb, 2008). The empirical study of place-based policies is challenging because benefited areas are usually distressed places, and are thus not randomly chosen. Researchers must therefore rely on non-experimental methods to study those policies, with difference-in-differences (DiD) being one of the main approaches (Baum-Snow and Ferreira, 2015).

A common threat to identification faced by non-experimental studies of place-based policies is the presence of treatment spillovers to non-targeted areas, which violates the (crucial) stable unit treatment value assumption (SUTVA) (Baum-Snow and Ferreira, 2015; Donaldson, 2015; Roth, Sant'Anna, Bilinski, et al., 2022a). As stated by Manski (1993), identifying a treatment effect under spillovers requires assumptions about the structure of the network. Following Manski's intuition, we can distinguish three types of situations in which the assumptions on the network structure may or may not justify the implementation of a difference-in-differences approach. First, when spillovers are very local, it can be reasonably assumed that distant areas experience no spillovers. In those cases, identification of the effects of the policy can be achieved by comparing the treated area versus distant ones (Delgado and Florax, 2015; Clarke, 2017; Butts, 2021). A prominent example of this approach is Kline and Moretti (2014a), who drop neighboring counties from their control group in their evaluation of the impact of the Tennessee Valley Authority (TVA).

In many economic settings, the mobility of economic agents between treated and untreated areas implies that truly untreated areas may not exist, or may be hard to credibly detect and justify. In those contexts, researchers may still recover the impact of the policy under the assumption that all areas are small enough such that the mobility of agents does not affect prices and quantities in non-treated areas. Busso, Gregory, and Kline (2013) constitute an example of this second type of situation in which difference-in-differences estimates can recover the effect of the policy.

A third type of situation occurs when the policy is large enough such that its effects extend to control areas. Consider, for instance, the case of common supply-side subsidies for housing construction which target entire neighborhoods in a given city, such as the Opportunity Zones program in the US. These policies redirect housing demand from non-subsidized into subsidized areas, resulting in depressed housing prices in non-subsidized areas. This effect of the policy on non-subsidized areas constitutes a violation of SUTVA, and thus invalidates difference-in-differences designs.

In this paper, we show that when a placed-based policy triggers substantial relocation from "non-treated" into "treated" areas, a difference-in-differences estimator includes three different effects, without being able to separately identify any of them. First, an "autarky effect" corresponds to treatment and control areas being in isolation, and therefore no relocation effects occur. Second, a "spillover effect" captures the effect of the inflow of agents into treated areas. Third, a "control unit contamination" captures the effect of the outflow of consumers from the control area on that area.

With a simple model of the supply and demand of housing in a city, we provide an analytical formula showing that the relative size of each of those three effects depends on the demand-side substitution patterns between neighborhoods as well as the supply elasticities of the neighborhoods. Importantly, more similar areas are likely to be closer demand-side substitutes, and therefore be subject to the highest contamination effects. This contradicts the intuition behind choosing very similar units to define treatment and control groups in difference-in-differences designs, including areas across policy borders (Neumark and Kolko, 2010).

Our methodological argument does not only shed light on which estimation strategy is appropriate for each context but also shows that different strategies may lead to opposite conclusions on the welfare impact of place-based policies. A basic insight from spatial equilibrium models is that the efficiency cost of these policies depends on the degree of mobility of economic agents between treated and untreated areas (Moretti, 2011; Kline and Moretti, 2014b). Thus, in contexts of substantial relocation between treated and untreated areas, empirical strategies maximizing the similarity across treatment and control units may exaggerate the deadweight loss of the policy.

We apply our methodological insights to a place-based policy giving substantial tax breaks for housing development in lagging areas of Montevideo, the capital city of Uruguay. Using administrative data on the universe of housing transactions in the city, we estimate a series of difference-in-differences with housing prices as our dependent variable. We find three difference-in-differences results that are consistent with our conceptual framework. First, when using all housing transactions in the city, we find a large negative effect of the policy of around 23% of the average transaction price. Second, when we follow the common practice of using only observations close to the border, estimates are very small negatives or zeros. Third, consistent with the presence of contamination effects, the absolute magnitude of these border estimates increases with a measure of heterogeneity between both sides of the border.

We further use our transaction data to estimate a structural model of the supply and demand of housing across Montevideo's neighborhoods. By solving for a series of counterfactual equilibria of the model, we show three main results. First, we compute a difference-in-differences term that recovers the true effect of the policy on the housing prices of treated areas. This is done by using the structure of the model to get rid of two sources of spurious correlation that enter the reduced-form difference-in-differences estimate. The first source of contamination is that the treatment can be correlated with the evolution of exogenous unobservables. A second source is the violation of SUTVA implied by the policy inducing households to relocate from unsubsidized to subsidized areas and depressing prices in unsubsidized areas as a result. Second, the model rationalizes our heterogeneous difference-in-differences estimates as being driven by demand-side substitution patterns **[not included in the current version]**. Third, the welfare impact of the policy differs sharply depending on the alternative difference-in-differences estimates **[not fully developed yet in the current version]**.

We model the demand for housing as the discrete choice problem of choosing a neighborhood within a city. The application of discrete choice techniques to spatial settings was pioneered by Bayer, Ferreira, and McMillan (2007) and has been applied to a variety of contexts, both within cities (Bayer, McMillan, et al., 2016; Almagro and Domınguez-Iino, 2019; Anagol, Ferreira, and Rexer, 2021) and across cities (Diamond, 2016; Alves, 2021). We estimate the price elasticity of the housing demand using the introduction of the tax break as an instrument. The housing supply in the model is characterized by a log-linear supply function for each neighborhood (Saiz, 2010; Diamond, 2016; Baum-Snow and Han, 2019). We estimate a common inverse supply elasticity for all neighborhoods by instrumenting housing quantities with a set of demand shifters obtained from our demand estimation. As is common in the quantitative spatial literature, our main insights from the model arise from solving for a set of counterfactual equilibria (Ahlfeldt et al., 2015; Donaldson, 2017; Monte, Redding, and Rossi-Hansberg, 2018; Caliendo, Dvorkin, and Parro, 2019; Fajgelbaum et al., 2019).

Our preliminary results show that our model fits the data well in terms of generating a difference-in-differences term that falls within a standard deviation of the reduced-form estimate. We highlight two preliminary results from our equilibrium counterfactuals. First, the existence of a spurious correlation between exogenous unobservables and the treatment causes the reduced-form difference-in-differences term to underestimate the share of the subsidy that reaches consumers by more than 20 percentage points. Second, although the policy causes prices to fall in unsubsidized areas, thus violating SUTVA, this source of contamination has a quantitatively minor role in our current estimates, only decreasing the share of the subsidy that reaches consumers by 1 percentage point. We expect this contamination arising from the SUTVA violation to play a much larger role in the difference-in-differences obtained comparing areas across the border of the policy. This expectation goes in line with our current reduced-form estimates, which show little or zero effects at the border, and is consistent with substitution patterns being more intense across both sides of the border. We have not yet computed our decomposition for the borders and only have done it for the whole city.

Our paper contributes to three main strands of literature. First, we contribute to the literature on causal inference in urban and regional economics. In their comprehensive review of this literature, Baum-Snow and Ferreira (2015) include difference-in-differences as one of the main techniques for obtaining causal estimates. The authors highlight how the re-sorting of individuals between treatment and control areas constitutes a serious threat to identification in difference-in-differences designs in spatial settings. This threat can be seen as a special case of dealing with spatial spillovers in difference-in-differences settings, a topic that has received attention from several previous works (Clarke, 2017; James and Smith, 2020; Butts, 2021; Huber and Steinmayr, 2021; Myers and Lanahan, 2022).

As discussed above, in some contexts spatial spillovers in difference-in-differences designs can be handled by defining large enough treatment and control units such that spillovers are contained within those units (Feyrer, Mansur, and Sacerdote, 2017; Huber and Steinmayr, 2021). In other contexts, previous works have suggested adding a series of difference-in-differences terms for successive "donuts" around the treatment area to flexibly capture the effect of the spillovers along different spatial (James and Smith, 2020; Butts, 2021; Myers and Lanahan, 2022). As spillovers eventually fade away far enough from the treatment, the comparison of treated areas against those spillover-free areas yields an average treatment effect on the treated (Clarke, 2017). However, when policies are large enough, those spillover-free areas may not exist or may be hard to credibly find. We provide a methodological framework to empirically study the effects of place-based policies in such contexts.

Second, we contribute to the literature on the evaluation of place-based policies that subsidize the development of lagging areas. As highlighted by Kline and Moretti (2014b), evaluating the success of these programs requires going beyond their impact on specific variables and adopting a consistent equilibrium framework. One key lesson from spatial equilibrium models is that the efficiency impact of place-based policies depends on the degree by which the policy induces economic agents to relocate from untreated into treated areas (Moretti, 2011; Busso, Gregory, and Kline, 2013; Serrato and Zidar, 2016). We show that the existence of heterogeneous mobility patterns of economic agents across areas can generate wrong conclusions about the efficiency of placed-based policies when estimates are obtained by comparing only certain areas.

Third, we contribute to the burgeoning literature on the methodological improvement of difference-in-differences estimates (Chaisemartin and D'Haultfœuille, 2021; Roth, Sant'Anna, Bilinski, et al., 2022a). Recently, there has been substantial progress in designs with multiple periods and variation in treatment timing (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Goodman-Bacon, 2021), potential violations in parallel trends (Rambachan and Roth, 2019; Roth and Sant'Anna, 2020), and improved inference (Ferman and Pinto, 2019). In their review of the state of the literature, Roth, Sant'Anna, Bilinski, et al. (2022b) include spillovers as one of the main areas for future research in this literature, with a special mention to spatial spillovers. We analyze a specific type of spatial spillover that we believe has high economic relevance. These are spillovers generated by the movement of economic agents across space in reaction to place-based policies. We stress the limitations of difference-in-differences designs in terms of recovering structural parameters of interest in those circumstances and show how structural methods can inform those estimates.

The paper continues with Section 2, presenting the context of the place-based policy we study and the data we use. Section 3 presents the set of difference-in-differences estimates obtained with alternative definitions of treatment and control areas. Section 4 presents the basic demand and supply framework that allows us to decompose the difference-in-differences estimates in three parts. Section 5 presents the structural model of the supply and demand for neighborhoods, while Section 6 presents how the model is estimated as well as subsequent results. In Section 7, we present the counterfactual equilibria of the model including the alternative welfare results obtained in each equilibrium. Section 8 concludes.

2 Institutional Context and Data

2.1 Institutional Context

The policy we analyze is a typical tax break for residential investment in lagging urban areas, similar to the Opportunity Zones (OZ) program in the US. We refer to the policy by its familiar acronym in Spanish of "LVIS" (*Ley de Vivienda de Interés Social*). Although the name of the policy refers to "The Promotion of Social Housing", in practice new homes that benefited from the program did not have to be occupied by low-income households.

Tax breaks in LVIS are quite large, especially compared to the OZ program in the US. González-Pampillón (2022) estimates that LVIS tax benefits were approximately equal to 20% of the total construction costs of the projects. The main component of those tax benefits is the total exemption from the country's corporate tax of 25%. Beyond this main component, LVIS units devoted to the rental market were also partially exempted from income and property tax on the rents. Because these tax breaks were so large, we expect a negative effect of the policy on the price of housing in subsidized areas relative to unsubsidized areas. In contrast to OZ tax breaks, which might be directed to commercial or residential development, LVIS tax breaks were only directed at residential development.

The law that created LVIS was approved by the Uruguayan parliament in August 2011. Its implementation details, including the designation of the subsidized zones, were only defined in October of that year. We thus take October 2011 as the starting date of the policy. The policy was substantially modified in June 2014, adding price ceilings and other restrictions that made it less attractive to investors. Because those changes would substantially change the impact of the policy on housing prices, we end our period of analysis in May 2014.

The mechanics of the law implied that developers had to apply for tax benefits, and obtain approval for their projects before beginning the construction phase. As a result, as shown by González-Pampillón (2022), the first few LVIS projects only reached completion by 2013, and the first sales of LVIS properties occurred in 2014, with most sales being made in the following years. We thus focus on a period when almost no projects were completed. This motivates us to abstract from the positive externalities of LVIS construction projects found by González-Pampillón (2022) (on housing prices) and Borraz et al. (2021) (on grocery prices).[1] Being able to disregard these positive spillovers of the policy on housing prices simplifies our analysis, and further reinforces our hypothesis of an expected negative effect of the policy on the housing prices in the subsidized area.[2] We focus our analysis on the impact of LVIS tax breaks in the department of Montevideo, which holds the homonymous 1.3 million capital city of Uruguay and concentrated 70% of the national total of LVIS projects (Berrutti, 2017). LVIS in Montevideo subsidized development in medium and low-income neighborhoods. Figure 1 presents a map of the subsidized and unsubsidized areas in the Montevideo department, together with the rural area which is irrelevant for our purposes. The area without subsidies is located along the southeast coast of the city, by the Rio de la Plata river. Most of the middle and high-income households live in this area. The subsidized area covers the majority of Montevideo's urban

[1] The positive externality on housing prices mirrors previous evidence by Baum-Snow and Marion (2009) and Diamond and McQuade (2018) for the LIHTC in the US.

[2] Housing prices reflect future rents, and these future rents could be positively affected by the spillovers of the new projects. González-Pampillón (2022) shows that these spillover effects of new LVIS projects are highly localized and decay after 200 meters. Based on this evidence, we argue that during our period of analysis, when basically no projects were constructed, it would be very hard to anticipate the location and impact of future projects. This leads us to ignore the effect of this type of spillover in our analysis.

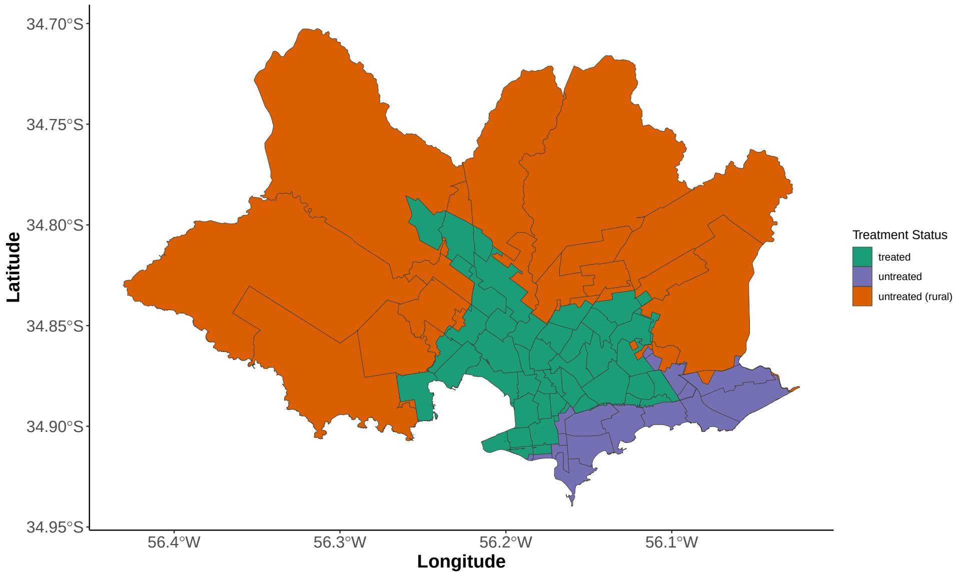

Figure 1: Montevideo by Treatment Status

area, including the central and older areas of the city as well as the working-class neighborhoods.

Due to the generosity of its tax breaks, the policy had huge impacts on the location of residential investment in Montevideo. Berrutti (2017) shows that the share of the subsidized area in terms of new square meters with construction permit went from around 20% before the policy to more than 60% in the first three years of the policy. Another measure of the huge quantitative relevance of the policy is the total amount of investments benefited by LVIS tax cuts. González-Pampillón (2022) estimates that the total investment approved during the first five years of the law amounts to 1.5% of the country's GDP.

2.2 Data

We use three main sources of data. The most important source is the universe of housing transactions from the National Registry Office in Uruguay for the period 2010-2014. This data includes the exact price and day for each housing sale. Uruguay is a high-income country according to the World Bank classification, and has the lowest levels of informality in the region. Also, within the country, Montevideo is the wealthiest and most developed city. This high level of development is consistent with our database of registered housing transactions, effectively being highly representative of the housing market of Montevideo.

The transaction data further includes a unique property number, which allows us to match that database with the registry of the National Cadaster of Uruguay, our second main source of data. This matching gives us the exact location of the parcel where the property is located and a set of housing characteristics, including the property area. The cadaster data does not exist for the years we analyze, and thus we use the earliest dataset available, which corresponds to 2016.

The third source of data is a geo-coded map of the areas subsidized by LVIS, similar to Figure 1. This geospatial data allows us to assign a subsidized or non-subsidized status to each housing transaction in the city, and to calculate exact distances to the borders of the policy.

Table 1 presents summary statistics on the housing transaction data for the three areas defined in Figure 1. The rural area has fewer transactions, much lower prices, and larger properties compared to the urban areas. Prices are lower in the subsidized than in the unsubsidized areas, which is consistent with the policy subsidizing lagging areas in the city. Housing prices grow over time in all areas because our years of study coincide with a period of strong economic growth in Uruguay.

In numerous empirical exercises in this paper, we use a set of variables to control for housing characteristics. These control variables are obtained from the cadaster data except for distance to the coast, which we computed using the exact location of the transaction. The set of controls from the cadaster includes the construction year as well as a set of categorical variables indicating construction category, construction condition, type of ceiling, and if there is ongoing construction work on the property. These variables were recorded by employees of the National Cadaster of Uruguay, and thus are objectively comparable across properties.

		Pre			Post		
		Treated	Untreated	Rural	Treated	Untreated	Rural
No. Obs.		10,240	6,688	764	14,673	9,289	1,245
Mean Square Meter Price (USD)							
	All Properties	700	1,413	226	957	1,864	349
		(493)	(662)	(359)	(659)	(843)	(461)
	Generic Housing Unit	349	951	154	579	1,412	300
		(175)	(181)	(103)	(228)	(257)	(98)
Mean Transaction Size (m^2)							
	All Properties	127	100	320	122	95	291
		(141)	(117)	(245)	(134)	(108)	(245)

Note: Standard deviations are provided in the parentheses.

Table 1: Summary Statistics by Pre-Post For All Regions

3 Difference-in-Differences Results

In this section, we present three sets of difference-in-differences (DiD) estimates of the effect of the policy. Taken together, these estimates illustrate two central points of the paper. First, DiD estimates of the effect of large placed-based policies on housing prices can vary greatly depending on the spatial range of included treatment and control units. Second, these estimates vary according to how similar treatment and control areas are from the point of view of consumers. This second point is fully consistent with the prediction of spatial equilibrium models in which the effect of a subsidy on housing prices depends on agents' mobility across subsidized and unsubsidized areas (Moretti, 2011; Busso, Gregory, and Kline, 2013).

The general specification for our difference-in-differences regressions is given by the following equation:

$$p_{ijt} = \gamma_j + \alpha_t + \beta Treat_j \times Post_t + f(X_{ijt}) + \epsilon_{ijt} \tag{1}$$

With i indicating a housing transaction, j the neighborhood, and t the month. We define neighborhoods in a way in which the whole area of each neighborhood is either treated or untreated. Thus, the neighborhood fixed effect γ_j already includes the $Treat_j$ term. p_{ijt} denotes the price per square meter for transaction i. X_{ijt} is a vector of housing characteristics.

	Dependent variable:					
	USD per Square Meter					
	(1)	(2)	(3)	(4)	(5)	(6)
Post × Treated	-158^{**}	-156^{**}	-155^{**}	-17	-70^{**}	-79^{*}
	(55)	(51)	(51)	(50)	(26)	(34)
Housing Characteristics	-	✓	✓	-	✓	✓
Fixed Effect(s)	-	-	Geo. Unit + Year	-	-	Geo. Unit + Year
No. Obs	42,899	42,899	42,899	7,841	7,841	7,841
Data	City-Wide	City-Wide	City-Wide	500m Buffer	500m Buffer	500m Buffer
Pre-Policy Generic Housing Unit - Mean USD per $m2$	685	685	685	795	795	795

$^{*} \ldots p < 0.05$ $^{**} \ldots p < 0.01$ $^{***} \ldots p < 0.001$
Note: Standard errors are clustered at the geographical unit level.
Note: Polynomial of degree three used to control for housing characteristics.

Table 2: DiD Regressions - USD per Square Meter

The first three columns of Table 2 present the estimates obtained when using all subsidized and unsubsidized areas as the treated and control groups, respectively. The first column only has the three basic binary variables in the spirit of the difference-in-differences design, namely indicating treatment group, treatment timing, and the interaction of these two. The second column adds a third-order polynomial on the housing characteristics described in Subsection 2.2. These include distance to the coast, construction year, and a set of categorical variables measuring the construction quality of the property. The last column adds a series of fixed effects indicating the year of the transaction and the neighborhood. The DiD estimates presented in Table 2 are complemented with graphical evidence in Figure A2. This figure plots the evolution of median prices per square meter in subsidized and unsubsidized areas after controlling for housing characteristics, as in Column (2) of Table 2.

The DiD estimates obtained when considering the whole city are consistently negative and stable in magnitude across the three different specifications in Table 2. This result is further confirmed by the graphical DiD analysis in the left panel of Figure A2. This figure also confirms the existence of parallel pre-trends between both areas. The magnitude of (-155) USD per square meter obtained in our preferred specification in Column (3) of Table 2 is quite large, representing 23% of the average price per square meter of a standardized unit of housing before the policy. This percentage falls in the range of González-Pampillón (2022)'s estimate on the tax break representing 20% of the value of the property. The similarity between both magnitudes further suggests that a relatively large share of the tax break was effectively passed on to consumers in the form of lower housing prices.

Columns (4) to (6) of Table 2 as well as the right panel of Figure A2 show that a very different conclusion on the effects of the policy would have emerged if we followed the common practice of looking at treatment and control areas along the border of the policy (Neumark and Kolko, 2010; Chen, E. Glaeser, and Wessel, 2022). Comparing areas across borders maximizes the similarity between the control and treatment groups, and thus minimizes the concerns about unobserved confounders. However, the flip side of achieving maximum similarity between areas is that consumers are most likely to easily substitute between them, leading to a very specific type of effect on prices, which in turn carries through to the conclusions regarding the policy's welfare effect.

The difference-in-differences estimates in Columns (4) to (6) of Table 2 compare subsidized and unsubsidized areas within a 500-meter buffer around the south-eastern border of the policy[3]. The right panel of Figure A2 presents the corresponding graphical evidence. Comparing the pre-policy price levels across both sides of the border in Figure A2 shows that both areas are very similar in terms of price per square meter. The figure further shows that the parallel trends assumption also holds when comparing these two areas. Our preferred point estimate in Column (6) of Table 2 shows an effect of (-79) USD per square meter, which amounts to around 10% of the pre-policy average within the 500-meter buffer.

According to the first two sets of DiD estimates, the policy caused a large reduction in housing prices in subsidized areas when looking at the whole city and a much smaller reduction when focusing on the 500-meter buffer across the policy's main border. As noted above, this pattern is fully consistent with the basic predictions of spatial equilibrium models. The third set of estimates further confirms this relationship between the magnitude of difference-in-differences estimates and the heterogeneity between the areas compared.

We explicitly introduce the role of heterogeneity by interacting our border DiD specification with an index of price differences between both sides of the border. Figure A3 illustrates how we compute this index: First, we define a large number

[3]Figure A1 in Appendix A provides a map of this buffer around the border.

of equidistant points along the main border of the policy. Second, we draw a 500-meter circle around each of those points and compute the difference in the median per-square meter price between the transactions that are contained in that circle but are on opposite sides of the border (left panel of Figure A3). As a result of this second step, each of the points along the border has a scalar value characterizing the heterogeneity in prices across the border at that point. The final step consists of attaching, to each housing transaction, a weighted average of those scalars, for which the transaction property lies within the respective 500-meter circles. The respective weights are the inverse of the distance between the transaction property and the applicable border points.

Table A1 in Appendix A presents the estimate on the interaction between the difference-in-differences term and the heterogeneity index. In this regression, we standardize the heterogeneity index by subtracting its average and dividing it by its standard deviation. The point estimate in Table A1 indicates that one standard deviation increase in border heterogeneity more than doubles the estimate on the (negative) effect of the policy on transaction prices. Figure A4 in Appendix A plots the relationship between the DiD estimate and the heterogeneity of the border for different values of the heterogeneity index with the corresponding 95% confidence intervals. The figure shows that the effect on prices is not statistically different from zero for a large segment of the left tail of the distribution of index values. This implies that border difference-in-differences estimates that maximize the comparability of control and treatment areas could lead to zero effects in contexts where the policy does have a substantial impact city-wide.

Results in this section thus show that DiD estimates of the price effects of a place-based policy strongly depend on the heterogeneity between the subsidized and unsubsidized areas chosen for comparison. The next section provides a simple conceptual framework for rationalizing these heterogeneous estimates and guiding empirical work.

4 Decomposition of DiD

At its very core, a difference-in-differences (DiD) estimator can be written in the following way:

$$\hat{\beta}_{DiD} = (y^{Post}_{Treated} - y^{Pre}_{Treated}) - (y^{Post}_{NotTreated} - y^{Pre}_{NotTreated}) \quad (2)$$

with y denoting the variable of interest. The change in the untreated observations is used to compute changes over time, which is then subtracted from the change in the treated observations in order to identify the policy's effect. In situations in which however all observational units are subject to the same (local) equilibrium forces, it can be shown that the DiD effect of the policy is actually a composite of several different (market) forces.

Without loss of generality, we will highlight the various components underlying the DiD estimator using a generic market for housing as our example. Moreover, we consider the price of housing, i.e. p_t^d, to be our variable of interest, and d denoting district and t denoting time. First, we will showcase two different demand patterns: no substitution (i.e. autarky), and perfect substitution. We then move on to our our generalised decomposition for two neighbourhoods. Please note that all examples abstract away from supply-side linkages, which however could easily be accommodated in this framework.

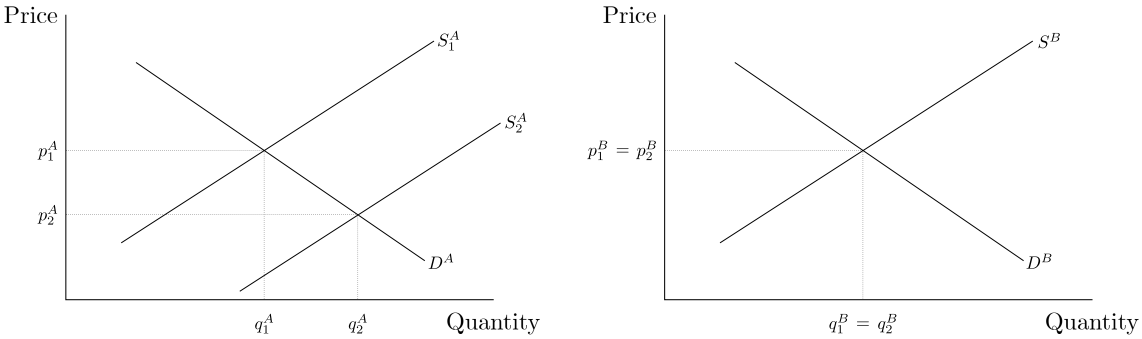

Figure 2: District A and District B are independent products

Figure 2 highlights a situation in which consumers are only willing to consider housing in one particular district $d \in \{A, B\}$, but not the other. Implementing a supply-side subsidy in district A would first shift supply outwards in district A. Because of lower prices, demand for housing in district A expands. Neither demand nor supply are affected in district B. The estimated DiD policy effect would be:

$$\hat{\beta}_{DiD}^{AUT} = (p_2^A - p_1^A) - (p_2^B - p_1^B) = p_2^A - p_1^A$$

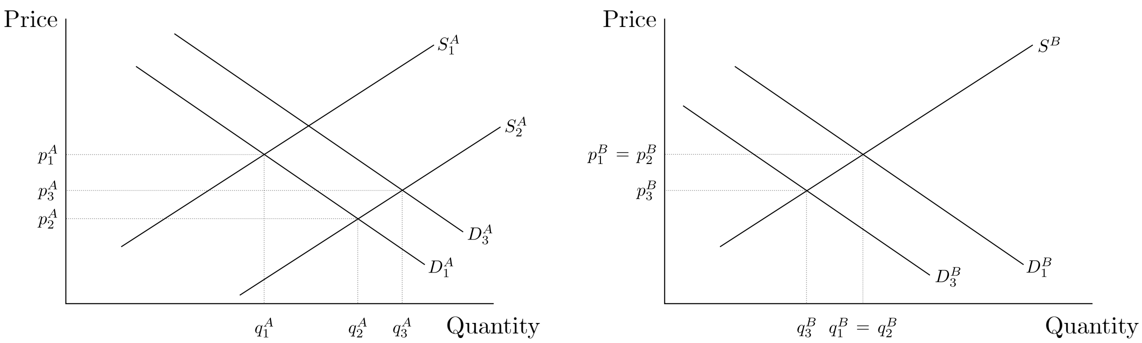

Figure 3: District A and District B are perfect substitutes

Figure 3 highlights a situation in which consumers consider housing in different districts to be perfect substitutes. Again, a supply-side policy is enacted in district A, pushing housing prices downwards. However, due to the assumed pattern of substitution, there is now an increase in district A prices because consumers from district B are switching locations. Consequentially, prices in B fall and prices in A rise. Estimating the effect of the same policy using the DiD approach now yields the following:

$$\begin{aligned}\hat{\beta}_{DiD} &= (p_3^A - p_1^A) - (p_3^B - p_1^B) \\ &= (p_3^A - p_2^A + p_2^A - p_1^A) - (p_3^B - p_2^B + p_2^B - p_1^B) \\ &= (p_2^A - p_1^A) + (p_3^A - p_2^A) - (p_3^B - p_2^B)\end{aligned}$$

We see that in the case of perfect substitution between different districts, the estimated DiD effect contains not only the autarky effect from before, but also the price increase due to higher demand for housing in the subsidized district A, as well as the price decrease in district B. As indicated in Equation 3, we call the additional demand effect in district A "(demand) spillovers", while the price change in district B is referred to as the "(control group) contamination".

$$\hat{\beta}_{DiD} = \underbrace{(p_2^A - p_1^A)}_{Autarky} + \underbrace{(p_3^A - p_2^A)}_{Spillovers} - \underbrace{(p_3^B - p_2^B)}_{Contamination} \tag{3}$$

Having discussed two extreme versions of demand patterns, we now impose slightly more economic structure to understand the estimated DiD effect in terms of demand and supply. We specify demand for housing in a particular district d at a given vector of market prices $\mathbf{p}$ by $D^d(\mathbf{p})$. Supply is specified by $S^d(q^d)$. With two neighbourhoods, of which one is subsidized while the other is not, the estimated DiD effect can be expressed by the following approximation:

$$\hat{\beta}_{DiD} \approx (p_2^A - p_1^A) \times \left[1 + \frac{\partial D^A}{\partial p^A} \times \left(\frac{\partial S^A}{\partial q^A} - \frac{\partial S^B}{\partial q^B} \times DR_{A,B}\right)\right] \tag{4}$$

Equation 4 highlights that any estimated DiD effect is actually a scaled version of the policy's effect in autarky. The scaling factor depends crucially on the responsiveness of demand and supply in the two districts, and also on the demand diversion ratio between the two. A full derivation of Equation 4 can be found in Appendix B.

If you were to extend the problem to two subsidized areas (districts A and C) and one unsubsidized area (district B), the estimated DiD effect can be written as:

$$\begin{aligned}
\hat{\beta}_{DiD} \approx\ & \underbrace{(p_2^A - p_1^A)}_{\beta_{DiD}^{AUT}} \\
& \underbrace{+ \frac{\partial S^A}{\partial q^A} \times \frac{\partial D^A}{\partial p^B} \times \frac{\partial S^B}{\partial q^B} \times \left[\frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A) + \frac{\partial D^B}{\partial p^C} \times (p_2^C - p_1^C)\right]}_{\textit{Spillover from B}} \\
& \underbrace{+ \frac{\partial S^A}{\partial q^A} \times \left[\frac{\partial D^A}{\partial p^C} \times (p_2^C - p_1^C) + \frac{\partial D^C}{\partial p^A} \times (p_2^A - p_1^A)\right]}_{\textit{Net Spillover from C}} \\
& \underbrace{- \frac{\partial S^B}{\partial q^B} \times \left[\frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A) + \frac{\partial D^B}{\partial p^C} \times (p_2^C - p_1^C)\right]}_{Contamination}
\end{aligned} \tag{5}$$

Equation 6 gives the generalized decomposition of the DiD estimator when there are multiple subsidized and unsubsidized areas.

$$\begin{aligned}
\hat{\beta}_{DiD} \approx\ & \underbrace{(p_2^A - p_1^A)}_{\beta_{DiD}^{AUT}} \\
& \underbrace{+ \frac{\partial S^A}{\partial q^A} \times \left(\sum_{u \in US} \frac{\partial D^A}{\partial p^u} \times \frac{\partial S^u}{\partial q^u} \times \left[\sum_{s \in S} \frac{\partial D^u}{\partial p^s} \times (p_2^s - p_1^s)\right]\right)}_{\textit{Spillover from Unsubsidized Area(s)}} \\
& \underbrace{+ \frac{\partial S^A}{\partial q^A} \times \left(\sum_{s \in S \setminus A} \frac{\partial D^A}{\partial p^s} \times (p_2^s - p_1^s)\right)}_{\textit{Spillover from other Subsidized Area(s)}} \\
& \underbrace{- \frac{\partial S^B}{\partial q^B} \times \left(\sum_{s \in S} \frac{\partial D^B}{\partial p^s} \times (p_2^s - p_1^s)\right)}_{\textit{Contamination from Reference Area}}
\end{aligned} \tag{6}$$

5 Structural Model

In this section we introduce a structural model of demand and supply that allow us to decompose difference-in-differences effects into the individual components mentioned in Section 4. The estimation results of the model are presented in Section 6 and Section 7 showcases a variety of counterfactuals which enable us to measure each of the individual components of the difference-in-differences term.

Geographically, our market is defined by the city limits of Montevideo, Uruguay. The time dimension of the market is defined by one calendar month. In order to make housing options comparable across different regions of Montevideo, we define a generic housing unit in terms of size and quality of construction. On the demand side, this allows us to focus exclusively on the problem of consumers choosing a neighbourhood in the city. On the supply side, it makes construction costs more comparable across neighborhoods.

5.1 Demand

The demand side of our structural model is composed of consumers who are making an exclusive choice regarding housing in different geographical areas of Montevideo. This discrete set of geographical areas is complemented by an additional option, namely that of staying at their current place of residence (i.e. the outside option). Consumers compare the utility of their options using Equation 7, and are assumed to choose the option that yields the highest indirect utility.

$$V_{ijt} = V(AM_{jt}, P_{jt}, \epsilon_{ijt}) \tag{7}$$

The first argument of the indirect utility function are the neighbourhood amenities AM_{jt}, consisting of neighbourhood characteristics that influence the vertical product differentiation. Examples of such could be time-invariant such as distance to the coast, prevailing winds, or major public infrastructure, or time-variant such as restaurants, shops, or public transportation schedules. The second argument is the price of the generic housing unit in neighbourhood j at time t, i.e. P_{jt}.

ϵ_{ijt}, the final argument of the indirect utility function, are individual specific preference shocks. While the amenities give rise to vertical product differentiation, these shocks give rise to horizontal product differentiation. This allows for consumers, who only differ in their ϵ vectors, to have different rankings of neighbourhoods.

We parameterize the indirect utility function with the following linear function:

$$V(AM_{jt}, P_{jt}, \epsilon_{ijt}) = A_j + B_t - \alpha \ln(P_{jt}) + \xi_{jt} + \epsilon_{ijt} = \delta_{jt} + \epsilon_{ijt} \tag{8}$$

We follow S. T. Berry (1994) in order to transform our theoretical discrete choice model into an empirically one. ξ_{jt} is assumed to be unobservable to the econometrician. ϵ is assumed to be i.i.d. across individuals, choices, and time, and is furthermore assumed to follow a Type I extreme value distribution with dispersion parameter $\sigma = 1$. It is also unobservable to the econometrician. Please note that the mean utility of the outside option is normalized to zero in every period, i.e. $\delta_{0t} = 0 \forall t$. Equation 9 is therefore the main demand estimating equation for our logit model, with s_j being the market share of area j at time t.

$$\ln(s_{j,t}) - \ln(s_{0,t}) = \delta_{jt} = A_j + B_t - \alpha \ln(P_{jt}) + \xi_{jt} \tag{9}$$

5.2 Supply

We model the supply side as perfectly competitive developers producing a total of H_{jt} generic housing units in neighborhood j at time t using labor, capital, and land.[4] The perfect competition assumption implies that housing prices - net of taxes - equal marginal costs:

$$P_{jt} = (1 - t_{jt}) * MC(CC_t(H_{jt}), LC_{jt}(H_{jt})). \tag{10}$$

The first argument of the marginal cost function are the construction costs, CC_t, which consist of the remuneration to capital and labor used in the production process. The price of capital depends on the national financial market and wages are determined in the country's highly centralized wage bargaining regime. The construction technology is the same in all neighborhoods at a given point in time. Thus, all the components of construction costs may vary over time but are the same across neighborhoods at any point in time.

LC_{jt} reflects the land costs that developers must pay to build housing. Land is owned by absentee landlords and is fixed in each neighborhood. As a result of this scarcity, land becomes more valuable with consumers' willingness to pay for living in the neighborhood. This force causes developers' marginal costs to increase with the number of units built in the neighborhood. Beyond this variable component, land rents also have a fixed neighborhood component L_j that reflects the time-invariant aspects of consumers' willingness to pay for the neighborhood as well as the total land available in each neighborhood.

We parameterize the marginal cost function as:

$$MC(CC_t(H_{jt}), LC_{jt}(H_{jt})) = CC_t \times L_j \times H_{jt}^{\gamma} \times \exp(\tilde{\epsilon}_{jt}) \tag{11}$$

Please note the addition of the marginal cost shock, i.e. $\tilde{\epsilon}_{jt}$, to the parameterization of marginal cost function. Applying the logarithm to both sides of Equation 11, and combining the resulting expression with Equation 10 yields our inverse housing supply curve:

$$\ln P_{jt} = \ln(1 - t_{jt}) + \ln CC_t + \ln L_j + \gamma \ln H_{jt} + \tilde{\epsilon}_{jt} \tag{12}$$

[4]The official data from the projects benefited by the LVIS tax benefit supports the assumption on perfect competition in the sector. The city-level market shares of developers in terms of housing units are very low, with an average below 0.5% and a maximum of less than 2%.

6 Estimation

6.1 Demand

Table 3 presents the ordinary least squares (Columns (1) and (2)) and instrumental variable (Columns (3) and (4)) estimates of Equation 9. We leverage the introduction of the LVIS policy as instrument to address the endogeneity of housing prices. This is a valid exogenous instrument given that the policy actually shifted construction costs.

The time-invariant amenities of neighbourhood j are captured by neighbourhood fixed effects [5]. Time-varying characteristics that affect all neighbourhood equally are captured by our time fixed effects.

	Dependent Variable:			
	$ln(s_{j,t}) - ln(s_{0,t})$			
	(1)	(2)	(3)	(4)
Logarithm of Price	-0.138	-0.164	-0.568^{***}	-2.015
	(0.086)	(0.127)	(0.089)	(1.234)
Method	OLS	OLS	IV	IV
Fixed Effect(s)	Geo. Unit + Month	Geo. Unit + Year × Month	Geo. Unit + Month	Geo. Unit + Year × Month
Outside Option	Not Buy	Not Buy	Not Buy	Not Buy
No. Obs	798	798	798	798
Data	Pre- and Post-Policy	Pre- and Post-Policy	Pre- and Post-Policy	Pre- and Post-Policy

* ... $p < 0.05$ ** ... $p < 0.01$ *** ... $p < 0.001$
Note: Standard errors are clustered at the geographical unit level.
Note: The cost-shifting instrument is the (Treatment × Post) DiD term.
Note: (Potential) market size is defined to be 2100.

Table 3: Structural Model - Demand Estimation

All estimates in Table 3 have the expected negative sign. For this preliminary version of the paper, we use the estimate in column 3 as our benchmark. We also use the regression errors plus the fixed effects from column 3 as a measure of amenities when we solve the model in the next section.

6.2 Supply

In this preliminary version, we have calibrated the two parameters of Equation 12. We calibrate the inverse supply elasticity to $\gamma = 0.1$ and following González-Pampillón (2022) we calibrate the subsidy amount to $t_{jt} = 0.2$ if, and only if, the area is included in the LVIS program and the point in time is after October 2011. Otherwise, $t_{jt} = 0$. By subtracting both calibrated terms from the left hand side, we are left with an aggregate measure of the marginal cost "intercept" that can be used in the various counterfactual scenarios which will be introduced in Section 7.

[5] Due to the relatively short time-frame in our data set, most amenities related to infrastructure, shops etc. can be assumed to be time-invariant.

7 Counterfactuals

This section presents three different equilibrium counterfactuals, using our structural model. These counterfactuals allow us to recover the effect of the policy on the subsidized areas, and to quantify the degree of contamination in our difference-in-differences (DiD) estimates.

Counterfactual results are presented in Table 4. The first two columns show the average price change in the unsubsidized (LVIS=0) and subsidized areas (LVIS=1). Price changes are computed by comparing the situation before and after the introduction of the subsidy programme. The third column uses Equation 2 and the two previous columns to simply compute the implied DiD estimate. Please note that this estimate stems from the structural model, and not from any DiD regression. The fourth column shows the dollar amount of the subsidy per square meter of a standard unit of housing. The final column shows the percentage of the subsidy that is appropriated by consumers in the form of lower prices. All columns refer to the unweighted average of all the subsidized and unsubsidized areas in the city. In this preliminary version of the paper, we do not have separate results for border and non-border neighborhoods, which will be present in a future version in order fully replicate our reduced-form DiD results.

	Average Price Change				
Counterfactual	LVIS Subsidy = 0	LVIS Subsidy = 1	DiD (structural)	Average Subsidy Amount	Average Incidence
CF 0 - Validation	430	236	−194	252	77%
CF 1 - Subsidy in a Pre World	−1.97	−153	−151	155	98%
CF 1′ - Subsidy in a Post World	−2.60	−250	−247	252	98%
CF 2 - Subsidy in Autarky	0	−153	−153	155	99%

Note: Stated numbers are in USD and for one square meter of a generic housing unit.

Table 4: Counterfactual Results

Each row in Table 4 presents a different counterfactual equilibrium. The first row, i.e. CF 0, aims at replicating the equilibria observed in the data. We use the policy introduction as a cut-off to separate the data into two components, then recover amenities and marginal costs for each, and subsequently solve for the respective equilibrium. This exercise is intended to validate our model in terms of being able to replicate the actual data. The difference-in-differences term obtained from this first counterfactual exercise (-194) falls within a standard deviation of our preferred reduced-form estimate (-155). The consumer incidence, i.e. the share of the subsidy appropriated by consumers, in this first counterfactual is 77%.

The second and third rows show two alternative ways of computing a counterfactual, which recovers the true effect of the policy on subsidized areas. In this counterfactual, we compute both equilibria, i.e. with and without the subsidy, using only pre-policy data (second row, CF 1), or using only post-policy data (third row, CF 1′). By keeping the exogenous elements of the model (i.e. amenities, and the quantity-invariant part of neighbourhood marginal costs) constant between the two equilibria, this counterfactual removes any spurious correlation between the aforementioned elements and the treatment that may otherwise affect the difference-in-differences term. Thus, the comparison of either of these two counterfactuals with CF 0 provides a measure of the role of contamination due to correlated exogenous unobservables in the DiD estimate. In both the second and third rows the incidence of the subsidy reaches 98%, more than 20 percentage points above the incidence in the first row. This suggests that the reduced-form DiD estimate could suffer from serious contamination due to the correlated evolution over time of exogenous factors with the treatment.

The fourth and final row of Table 4 helps us shed light on the role of additional demand spillovers. We do this by computing an equilibrium in which consumers are not allowed to switch between neighbourhoods after the introduction of the policy. They are therefore restricted to either "re-buy" housing in the same neighbourhood as before, or decide not to buy. By definition, the change in prices in the unsubsidized areas, i.e. the second column of Table 4, is zero[6]. The comparison with CF 1 allows us to quantify the contamination coming from consumers substituting from unsubsidized into subsidized areas.

The comparison between CF 1 and CF 2 allows us to separately identify the three components of Equation 3. First, the LVIS=1 column in CF 2 recovers the effect of the policy on the subsidized areas in autarky. Second, the difference between CF 1 and CF 2 along the LVIS=1 column recovers the effect of spillovers of the policy on the subsidized areas. This effect is negligible in our current calculations. Finally, the difference between CF 1 and CF 2 along the LVIS=0 column recovers the contamination effect due to the SUTVA violation. This contamination is small and represents around 2 dollars per square meter of standard unit of housing.

We expect that our future estimation of a richer demand model in the spirit of S. Berry, Levinsohn, and Pakes (1995) will yield higher contamination from both sources, as it will allow for better substitution between similar products. This is particularly true when computing this decomposition at the treatment border, on which many empirical studies are focused, as consumers substitute more easily across similar sides of the border.

8 Conclusion

The non-random assignment of place-based policies implies that their study requires the use of quasi-experimental methods, with difference-in-differences (DiD)

[6]From the perspective of consumers in these areas nothing changed: marginal costs of housing within these areas remain constant, and thus no consumer is re-evaluating his/her decision.

being one of the most important. In this paper, we provide a framework to analyze when difference-in-differences estimates may or may not recover the effect of the policy. In contexts where place-based policies are large enough to affect non-targeted areas, reduced-form methods may not recover the actual effect of the policy. We provide a structural framework to recover - in those contexts - the effects on quantities, prices, and welfare.

We illustrate the potential of our framework by analyzing a large tax break for housing development in lagging areas in Montevideo. We show that reduced-form difference-in-differences vary greatly depending on the spatial range of included treatment and control units. This variation, in turn, follows the pattern predicted by our framework: When the control and treated groups are more similar, the effect of the tax break on prices is lower. According to our framework, these heterogeneous results are not necessarily capturing an underlying heterogeneity in the effects of the policy but partly reflect a heterogeneity in the degree of demand spillovers and reference-group contamination across the different estimates.

Our preliminary results from the equilibrium counterfactuals show that the reduced-form difference-in-differences estimates for the whole city substantially underestimate the benefit that consumers obtain from the tax break. The decomposition of the sources of contamination shows that the correlation between exogenous unobservables and the treatment is the main source. The violation of SUTVA due to agents moving away from unsubsidized areas as a result of the policy plays a minor role.

References

Ahlfeldt, Gabriel M., Stephen J. Redding, Daniel M. Sturm, and Nikolaus Wolf (Nov. 2015). "The Economics of Density: Evidence From the Berlin Wall". In: *Econometrica* 83, pp. 2127–2189.

Almagro, Milena and Tomás Dominguez-Iino (2019). "Location sorting and endogenous amenities: Evidence from amsterdam". In: *NYU, mimeograph*.

Alves, Guillermo (Mar. 2021). "Slum growth in Brazilian cities". en. In: *Journal of Urban Economics* 122, p. 103327. ISSN: 0094-1190. DOI: `10.1016/j.jue.2021.103327`.

Anagol, Santosh, Fernando Ferreira, and Jonah M. Rexer (Oct. 2021). *Estimating the Economic Value of Zoning Reform*. Working Paper. DOI: `10.3386/w29440`.

Baum-Snow, Nathaniel and Fernando Ferreira (2015). "Causal inference in urban and regional economics". In: *Handbook of regional and urban economics*. Vol. 5. Elsevier, pp. 3–68.

Baum-Snow, Nathaniel and Lu Han (2019). "The microgeography of housing supply". In: *Work in progress, University of Toronto*.

Baum-Snow, Nathaniel and Justin Marion (2009). "The effects of low income housing tax credit developments on neighborhoods". en. In: *Journal of Public Economics* 93.5-6, pp. 654–666.

Bayer, Patrick, Fernando Ferreira, and Robert McMillan (2007). "A Unified Framework for Measuring Preferences for Schools and Neighborhoods". In: *Journal of Political Economy* 115.4, pp. 588–638.

Bayer, Patrick, Robert McMillan, Alvin Murphy, and Christopher Timmins (2016). "A Dynamic Model of Demand for Houses and Neighborhoods". In: *Econometrica* 84.3. Publisher: [Wiley, The Econometric Society], pp. 893–942. ISSN: 0012-9682.

Berrutti, Felipe (2017). "Place-based subsidies and location decisions: The case of Uruguay". In: *Revista de Economía* 24.1. Publisher: Banco Central del Uruguay.

Berry, Steven, James Levinsohn, and Ariel Pakes (1995). "Automobile prices in market equilibrium". In: *Econometrica: Journal of the Econometric Society*, pp. 841–890.

Berry, Steven T. (1994). "Estimating discrete-choice models of product differentiation". In: *The RAND Journal of Economics*, pp. 242–262.

Borraz, Fernando, Felipe Carozzi, Nicolas Gonzalez-Pampillon, and Leandro Zipitria (July 2021). *Local Retail Prices, Product Varieties and Neighborhood Change*. en. SSRN Scholarly Paper. Rochester, NY.

Busso, Matias, Jesse Gregory, and Patrick Kline (Apr. 2013). "Assessing the Incidence and Efficiency of a Prominent Place Based Policy". In: *American Economic Review* 103.2, pp. 897–947. ISSN: 0002-8282. DOI: `10.1257/aer.103.2.897`.

Butts, Kyle (Nov. 2021). *Difference-in-Differences Estimation with Spatial Spillovers*. Number: arXiv:2105.03737 arXiv:2105.03737 [econ]. DOI: 10.48550/arXiv.2105.03737.

Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro (2019). "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock". en. In: *Econometrica* 87.3, pp. 741–835. ISSN: 1468-0262. DOI: 10.3982/ECTA13758.

Callaway, Brantly and Pedro H. C. Sant'Anna (Dec. 2021). "Difference-in-Differences with multiple time periods". en. In: *Journal of Econometrics*. Themed Issue: Treatment Effect 1 225.2, pp. 200–230. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2020.12.001.

Chaisemartin, Clément de and Xavier D'Haultfœuille (Dec. 2021). *Two-Way Fixed Effects and Differences-in-Differences with Heterogeneous Treatment Effects: A Survey*. en. SSRN Scholarly Paper. Rochester, NY. DOI: 10.2139/ssrn.3980758.

Chen, Jiafeng, Edward Glaeser, and David Wessel (Apr. 2022). "JUE Insight: The (non-)effect of opportunity zones on housing prices". en. In: *Journal of Urban Economics*, p. 103451. ISSN: 0094-1190. DOI: 10.1016/j.jue.2022.103451.

Clarke, Damian (Sept. 2017). *Estimating Difference-in-Differences in the Presence of Spillovers*. en. Tech. rep. 81604. Publication Title: MPRA Paper. University Library of Munich, Germany.

Delgado, Michael S. and Raymond J. G. M. Florax (Dec. 2015). "Difference-in-differences techniques for spatial data: Local autocorrelation and spatial interaction". en. In: *Economics Letters* 137, pp. 123–126. ISSN: 0165-1765. DOI: 10.1016/j.econlet.2015.10.035.

Diamond, Rebecca (2016). "The Determinants and Welfare Implications of US Workers' Diverging Location Choices by Skill: 1980-2000". In: *American Economic Review* 106.3, pp. 479–524. DOI: 10.1257/aer.20131706.

Diamond, Rebecca and Tim McQuade (Oct. 2018). "Who Wants Affordable Housing in their Backyard? An Equilibrium Analysis of Low Income Property Development". In: *Journal of Political Economy*. ISSN: 0022-3808. DOI: 10.1086/701354.

Donaldson, Dave (2015). "The Gains from Market Integration". In: *Annual Review of Economics* 7.1, pp. 619–647. DOI: 10.1146/annurev-economics-080213-041015.

– (2017). "Railroads of the Raj: Estimating the impact of transportation infrastructure". In: *American Economic Review*.

Fajgelbaum, Pablo D., Eduardo Morales, Juan Carlos Suárez Serrato, and Owen Zidar (Jan. 2019). "State Taxes and Spatial Misallocation". en. In: *The Review of Economic Studies* 86.1. Publisher: Oxford Academic, pp. 333–376. ISSN: 0034-6527. DOI: 10.1093/restud/rdy050.

Ferman, Bruno and Cristine Pinto (2019). "Inference in Differences-in-Differences with Few Treated Groups and Heteroskedasticity". en. In: *The Review of Economics and Statistics* 101.3. Publisher: MIT Press, pp. 452–467.

Feyrer, James, Erin T. Mansur, and Bruce Sacerdote (Apr. 2017). "Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution". en. In: *American Economic Review* 107.4, pp. 1313–1334. ISSN: 0002-8282. DOI: 10.1257/aer.20151326.

Glaeser, Edward L. and Joshua D. Gottlieb (2008). "The Economics of Place-Making Policies". In: *Brookings Papers on Economic Activity* 2008. Publisher: Brookings Institution Press, pp. 155–239. ISSN: 0007-2303.

González-Pampillón, Nicolás (Jan. 2022). "Spillover effects from new housing supply". en. In: *Regional Science and Urban Economics* 92, p. 103759. ISSN: 0166-0462. DOI: 10.1016/j.regsciurbeco.2021.103759.

Goodman-Bacon, Andrew (Dec. 2021). "Difference-in-differences with variation in treatment timing". en. In: *Journal of Econometrics*. Themed Issue: Treatment Effect 1 225.2, pp. 254–277. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2021.03.014.

Huber, Martin and Andreas Steinmayr (Apr. 2021). "A Framework for Separating Individual-Level Treatment Effects From Spillover Effects". In: *Journal of Business & Economic Statistics* 39.2. Publisher: Taylor & Francis, pp. 422–436. ISSN: 0735-0015. DOI: 10.1080/07350015.2019.1668795.

James, Alexander G. and Brock Smith (June 2020). "Geographic Dispersion of Economic Shocks: Evidence from the Fracking Revolution: Comment". en. In: *American Economic Review* 110.6, pp. 1905–1913. ISSN: 0002-8282. DOI: 10.1257/aer.20180888.

Kline, Patrick and Enrico Moretti (Jan. 2014a). "Local Economic Development, Agglomeration Economies, and the Big Push: 100 Years of Evidence from the Tennessee Valley Authority". en. In: *The Quarterly Journal of Economics* 129.1, pp. 275–331. ISSN: 0033-5533, 1531-4650. DOI: 10.1093/qje/qjt034.

– (2014b). "People, Places, and Public Policy: Some Simple Welfare Economics of Local Economic Development Programs". In: *Annual Review of Economics* 6.1, pp. 629–662.

Manski, Charles F. (1993). "Identification of Endogenous Social Effects: The Reflection Problem". In: *The Review of Economic Studies* 60.3. Publisher: [Oxford University Press, Review of Economic Studies, Ltd.], pp. 531–542. ISSN: 0034-6527. DOI: 10.2307/2298123.

Monte, Ferdinando, Stephen J. Redding, and Esteban Rossi-Hansberg (Dec. 2018). "Commuting, Migration, and Local Employment Elasticities". en. In: *American Economic Review* 108.12, pp. 3855–3890. ISSN: 0002-8282. DOI: 10.1257/aer.20151507.

Moretti, Enrico (2011). *Local Labor Markets*. Handbook of Labor Economics. Elsevier, pp. 1237–1313.

Myers, Kyle R. and Lauren Lanahan (July 2022). "Estimating Spillovers from Publicly Funded R&D: Evidence from the US Department of Energy". en. In: *American Economic Review* 112.7, pp. 2393–2423. ISSN: 0002-8282. DOI: 10.1257/aer.20210678.

Neumark, David and Jed Kolko (July 2010). "Do enterprise zones create jobs? Evidence from California's enterprise zone program". en. In: *Journal of Urban Economics* 68.1, pp. 1–19. ISSN: 0094-1190. DOI: 10.1016/j.jue.2010.01.002.

Rambachan, Ashesh and Jonathan Roth (2019). "An honest approach to parallel trends". In: *Unpublished manuscript, Harvard University*.

Roth, Jonathan and Pedro HC Sant'Anna (2020). "When is parallel trends sensitive to functional form?" In: *arXiv preprint arXiv:2010.04814*.

Roth, Jonathan, Pedro HC Sant'Anna, Alyssa Bilinski, and John Poe (2022a). "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature". In: *arXiv preprint arXiv:2201.01194*.

– (Jan. 2022b). "What's Trending in Difference-in-Differences? A Synthesis of the Recent Econometrics Literature". en. In: *Papers*. Number: 2201.01194 Publisher: arXiv.org.

Saiz, Albert (Jan. 2010). "The Geographic Determinants of Housing Supply". en. In: *The Quarterly Journal of Economics* 125.3, pp. 1253–1296. ISSN: 0033-5533, 1531-4650. DOI: 10.1162/qjec.2010.125.3.1253.

Serrato, Juan and Owen Zidar (Sept. 2016). "Who Benefits from State Corporate Tax Cuts? A Local Labor Markets Approach with Heterogeneous Firms". In: *American Economic Review* 106.9, pp. 2582–2624. ISSN: 0002-8282. DOI: 10.1257/aer.20141702.

Sun, Liyang and Sarah Abraham (Dec. 2021). "Estimating dynamic treatment effects in event studies with heterogeneous treatment effects". en. In: *Journal of Econometrics*. Themed Issue: Treatment Effect 1 225.2, pp. 175–199. ISSN: 0304-4076. DOI: 10.1016/j.jeconom.2020.09.006.

A Appendix: Figures and Tables

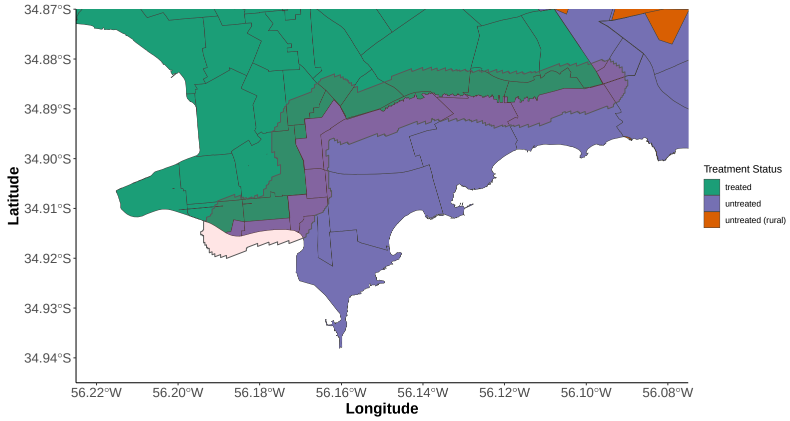

Figure A1: Montevideo by Treatment Status - 500m Buffer

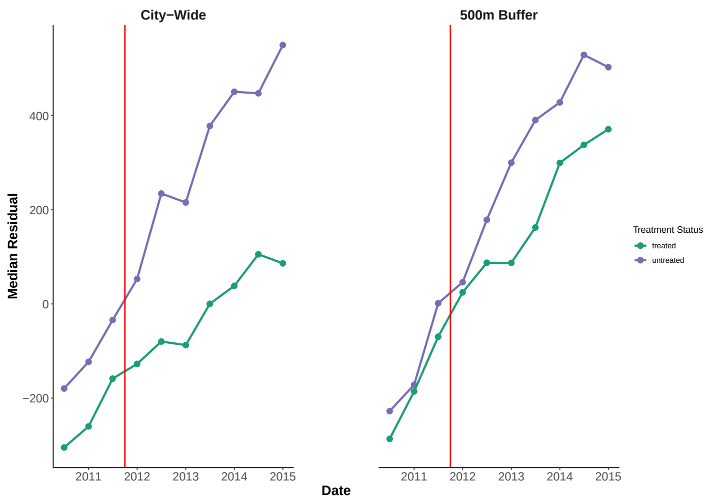

Figure A2: Difference-in-Differences Pre-Trends over Time by Treatment Status

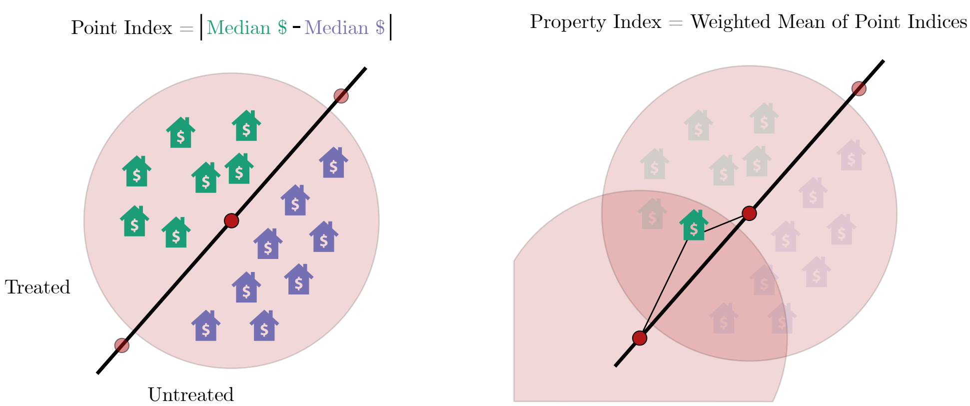

Figure A3: How Border Z-Scores are Computed

	Dependent Variable:	
	USD per Square Meter	
	(1)	(2)
Post × Treated	-79^{*}	-94^{**}
	(34)	(33)
Post × Treated × Z-Score	-	-126^{*}
		(50)
Housing Characteristics	✓	✓
Fixed Effect(s)	Geo. Unit + Year	Geo. Unit + Year
No. Obs	7,841	7,668
Data	500m Buffer	500m Buffer

* $\ldots p < 0.05$ ** $\ldots p < 0.01$ *** $\ldots p < 0.001$

Note: Standard errors are clustered at the geographical unit level.

Note: Polynomial of degree three used to control for housing characteristics.

Table A1: DiD Regressions - USD per Square Meter with Heterogeneity

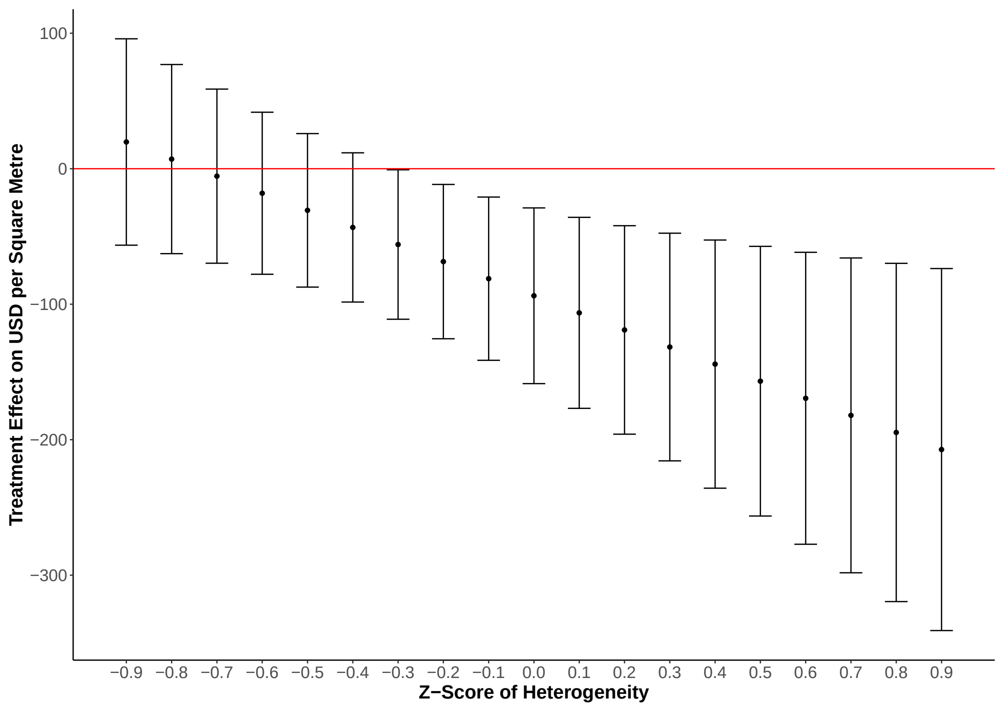

Figure A4: Estimated Treatment Effect as a Function of Heterogeneity

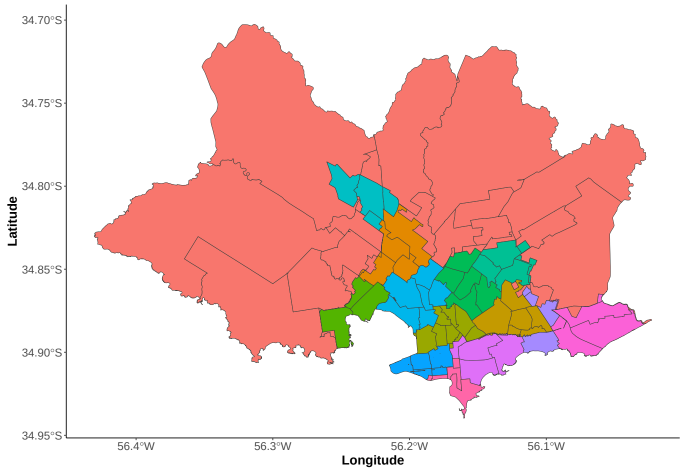

Figure A5: Montevideo by Geographical Unit for Structural Model

B Appendix: Deriving the DiD Decomposition

We specify demand for housing in a particular district d at given prices $\mathbf{p}$ by $D^d(\mathbf{p})$. Supply is specified by $S^d(q^d)$. Please note that this illustration makes use of a linear approximation in both cases.

B.1 One Subsidized Area

The shift in equilibrium housing quantity in district B in response to the initial policy-induced price change in district A is approximated in the following way:

$$q_3^B - q_2^B = \frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A)$$

A similiar statement can be made about the equilibrium housing quantity in district A.

$$q_3^A - q_2^A = \frac{\partial D^A}{\partial p^A} \times (p_2^A - p_1^A)$$

Relying on the assumption of full competition within each district, changes in equilibrium housing prices in both districts can be approximated.

$$p_3^A - p_2^A = \frac{\partial S^A}{\partial q^A} \times (q_3^A - q_2^A)$$

$$p_3^B - p_2^B = \frac{\partial S^B}{\partial q^B} \times (q_3^B - q_2^B)$$

Inserting the two earlier equations into the latter equations, we can express second-round equilibrium price changes as a function of demand and supply partial derivatives, as well as the initial policy-induced price change in district A.

$$p_3^A - p_2^A = \frac{\partial S^A}{\partial q^A} \times \frac{\partial D^A}{\partial p^A} \times (p_2^A - p_1^A)$$

$$p_3^B - p_2^B = \frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A)$$

Inserting these two expressions into the generalised version of the DiD estimator given in Equation 3, we arrive at Equation 4 presented in Section 4.

$$\begin{aligned}
\hat{\beta}_{DiD} &= (p_2^A - p_1^A) + (p_3^A - p_2^A) - (p_3^B - p_2^B) \\
&\approx (p_2^A - p_1^A) + \frac{\partial S^A}{\partial q^A} \times \frac{\partial D^A}{\partial p^A} \times (p_2^A - p_1^A) - \frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A) \\
&= (p_2^A - p_1^A) \times \big[1 + \frac{\partial S^A}{\partial q^A} \times \frac{\partial D^A}{\partial p^A} - \frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^A}\big] \\
&= (p_2^A - p_1^A) \times \big[1 + \frac{\partial D^A}{\partial p^A} \times \big(\frac{\partial S^A}{\partial q^A} - \frac{\partial S^B}{\partial q^B} \times DR_{A,B}\big)\big]
\end{aligned}$$

with $DR_{A,B}$ being the diversion ratio between housing in district A and housing in district B.

B.2 Two Subsidized Areas

Using again the notation from Subsection B.1, we now add a second subsidized district C.

$$dD^B = \frac{\partial D^B}{\partial p^A}(p_2^A - p_1^A) + \frac{\partial D^B}{\partial p^C}(p_2^C - p_1^C)$$

$$dD^A = \frac{\partial D^A}{\partial p^B} dP^B + \frac{\partial D^A}{\partial p^C}(p_2^C - p_1^C)$$

$$dD^C = \frac{\partial D^C}{\partial p^A}(p_2^A - p_1^A) + \frac{\partial D^C}{\partial p^B} dP^B$$

Using the supply equation, we can derive an expression for dP^B:

$$
\begin{aligned}
dP^B &= \frac{\partial S^B}{\partial q^B} dD^B \\
&= \frac{\partial S^B}{\partial q^B} \times \left[\frac{\partial D^B}{\partial p^A}(p_2^A - p_1^A) + \frac{\partial D^B}{\partial p^C}(p_2^C - p_1^C)\right]
\end{aligned}
$$

Using the same approach for the price change in district A, we get the following:

$$
\begin{aligned}
dP^A =& \frac{\partial S^A}{\partial q^A} dD^A \\
=& \frac{\partial S^A}{\partial q^A} \times \left[\frac{\partial D^A}{\partial p^B} dP^B + \frac{\partial D^A}{\partial p^C}(p_2^C - p_1^C)\right] \\
=& \frac{\partial S^A}{\partial q^A} \times \left[\frac{\partial D^A}{\partial p^B} \times \left(\frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A) + \frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^C} \times (p_2^C - p_1^C)\right) + \right. \\
& \left. \frac{\partial D^A}{\partial p^C}(p_2^C - p_1^C)\right]
\end{aligned}
$$

We can now re-write the DiD estimator:

$$
\begin{aligned}
\hat{\beta}_{DiD} =& (p_3^A - p_1^A) - (p_3^B - p_1^B) \\
=& (p_3^A - p_2^A) + (p_2^A - p_1^A) - (p_3^B - p_2^B) \\
\approx& (p_2^A - p_1^A) + \\
& \frac{\partial S^A}{\partial q^A} \times \left[\frac{\partial D^A}{\partial p^B} \times \left(\frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^A} \times (p_2^A - p_1^A) + \frac{\partial S^B}{\partial q^B} \times \frac{\partial D^B}{\partial p^C} \times (p_2^C - p_1^C)\right) + \right. \\
& \left. \frac{\partial D^A}{\partial p^C}(p_2^C - p_1^C)\right] + \\
& \frac{\partial S^B}{\partial q^B} \times \left[\frac{\partial D^B}{\partial p^A}(p_2^A - p_1^A) + \frac{\partial D^B}{\partial p^C}(p_2^C - p_1^C)\right]
\end{aligned}
$$

Please note:

1. The first term is the autarky effect.
2. The second term is the spillovers effects. In this case, the spillovers effect in equilibrium can be negative or positive. They are going to depend on the two exogenous changes. Spillovers can attenuate the autarky effect if the net effect is to bring people to A, or increase it if the net effect is to send people to C (A gains from B, but loses to C).
3. The third term is the contamination effect, and is similar to before but now

it is increased compared to the previous example when only one region receives the subsidy (the reason is that B now changes because people are leaving to A but also because people are leaving to C)