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An Analysis of the Process of Disinflationary Structural Change: The Case of Mexico*

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Abstract

I study the diffusion process of permanent disinflationary shocks in the Mexican economy using disaggregated price data for 283 goods across 46 cities in the period 1995-2012. I first show that the distribution of shocks shows considerable heterogeneity, with more than 80 % of all cases having experienced a break. I then show that both the likelihood and timing are spatially correlated across cities, and find a positive and concave relationship between CPI weights and the likelihood and timing of a break. These findings suggest that the process of structural change follows a diffusion process across the spatial and goods dimensions.
Keywords: Structural change, inflation, spatial econometrics, trend-stationary, emerging economy, Mexico.
JEL Classification: E30, E31, N16, N26, O54,C21, C22, C24.

Resumen

En este trabajo estudio el proceso de difusión de choques permanentes de reducción de la inflación en la economía mexicana utilizando series de precios desagregadas para 283 bienes y 46 ciudades en el período 1995-2012. Muestro primero que la distribución de los choques es considerablemente heterogénea, con más del 80 % de todos los casos habiendo experimentado un quiebre. A continuación muestro que tanto la probabilidad como la temporalidad de los choques están correlacionados espacialmente entre ciudades, y encuentro una relación positiva y cóncava entre las ponderaciones utilizadas en el cálculo del INPC y la probabilidad y temporalidad de los choques. Estos resultados sugieren que el proceso de cambio estructural sigue un proceso de difusión en las dimensiones espaciales y de productos.
Palabras Clave: Cambio estructural, inflación, econometría espacial, estacionariedad con tendencia, economías emergentes, México.

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1 Introduction

It is now well established that Mexico experienced a steady reduction in CPI inflation during the second half of the 1990s. For example, Ramos-Francia and Torres García (2005) argue that the stabilization programs introduced during the aftermath of the 1994-1995 crisis (preventing a situation of fiscal dominance) along with the steady transition toward a system of inflation targeting allowed the Bank of Mexico to reduce inflation from the 1995 post-crisis 51% level to a neighborhood of the long-run 3% inflation target in recent years.[1,2]

Several empirical studies have provided estimates of the timing of the breaks that Mexican inflation experienced in the late 1990s and early 2000s. Using quarterly percent change in consumer prices, Capistrán and Ramos-Francia (2009) show that there was decrease in average (or level) inflation in the first quarter of 1999. Moreover, this change in the level was accompanied by a change in persistence, reduced from the period 1988-1999 to the 1999-2007 period. Similarly, using monthly inflation, Chiquiar, Noriega, and Ramos-Francia (2010) test for a change in persistence and find evidence for a change from a non-stationary to a stationary regime between December, 2000 and April, 2001 for headline and core inflation, respectively.

However, since CPI is a weighted average of price indices for different goods and services and across cities, these findings shed no light onto the process of structural change or its determinants at the more disaggregated level. Moreover, by construction, it is hard or even impossible to interpret these aggregate results; e.g. if a break was found, does it mean that *on average* all prices experienced a break around the same date? If the answer is

[1] Yearly CPI inflation in 2012 was 3.57%.

[2] The official announcement that the Bank of Mexico would implement an inflation target system was made in 2001. In 2002 the long-term 3% inflation target was set. A thorough description of the process can be found in Ramos-Francia and Torres García (2005).

positive one may then hypothesize that a *common* shock caused the break. Alternatively, it is likely that the timing and occurrence of a break was unevenly distributed across the spatial and goods dimensions, in which case, the analysis of such distributions should improve our understanding of the actual process of structural change.

In this paper I seek to establish the properties of persistence of the stochastic processes followed by the rate of change of price indexes at the most disaggregated level possible. The paper is descriptive in nature, and my aim at this point is only to collect several facts about the process of structural change in an economy such as Mexico. To be sure, I focus on "genéricos" , i.e. groups of goods and services with similar characteristics that are the fundamental building blocks in the construction of CPI inflation. Using price indices for this sample of 283 goods and services across 46 Mexican cities January 1995 to December 2012, I first test whether each of the micro data yearly inflation rates follows a trend-stationary stochastic process with possibly multiple breaks and then estimate the determinants of the diffusion process for both the estimated likelihood of experiencing a break and for the corresponding timing. To clarify the language from the outset, I say that a vector of stochastic processes $\{y_{c,t}\}$ follows a spatial diffusion if the correlation between between two units c and c' in two different time periods t and t' is a function of the Euclidean distance between the units.[3]

To motivate the study and to provide a first glimpse at the results, Panel A in Figure (1) shows yearly CPI inflation rate for the period under study along with the corresponding estimated break date, understood as a change in the trend function such that the resulting process is stationary. The results are in line with those in the previous literature: Mexican CPI inflation experienced a structural break — defined as a statistically significant change in the parameters governing the trend function — between 2001 and 2002. Panel B,

[3]To be sure, if the function does not depend on time, the stochastic process is stationary on the time dimension.

however, displays the estimated kernel density of the timing of the breaks *conditional on experiencing a break*, i.e. excluding all of the cases where I could not reject the hypothesis of a unit root. It can be readily seen that there is considerable heterogeneity in the timing of the breaks, and most importantly, on the actual occurrence of the event. In this paper I first document this heterogeneity and later exploit it to understand the process of structural change.

I first find that there is substantial variation in the likelihood and timing of structural breaks at the micro data level. For those goods and services (across all cities) that experience a break, the earliest and latest breaks were estimated at the beginning of 1996 and 2012, respectively, i.e. spreading through the whole period under study. Interestingly, the *median* estimated break date is a better approximation of the structural break found for CPI inflation than the corresponding mean, i.e. it does not follow that the break date of an average is the average of the corresponding structural breaks. For the remaining 20% of goods and services I cannot reject the null hypothesis of a unit root against the alternative of trend-stationarity with as many as ten breaks in the trend function.

Using the estimated likelihood and timing of structural change I then estimate regressions akin to diffusion processes on the spatial and goods dimension. I find first that both the likelihood and timing of the breaks are positively correlated on the spatial dimension, implying, for example, that it is more likely for a particular good in a specific city to experience a break if the same is happening for neighboring cities, i.e. consistent with a spatial diffusion of (dis) inflationary shocks.

Since I lack an objective proximity measure for different goods I use two alternative approaches: first, I control for core and non-core groups fixed effects using the goods and services classifications elaborated by the Instituto Nacional de Estadística y Geografía (INEGI). In addition, I control for expenditure CPI weights. The most striking result here is the existence of an increasing and concave relation between the likelihood of a break and the CPI weights, i.e. those goods and services that take a larger share of the households' consumption expenditure were more likely to experience a break. Moreover, conditional on experiencing a break, these goods took longer to experience the structural change. While I cannot identify supply and demand-side causation— i.e. whether the break was caused by a change in household or firms behavior—, this finding is of some interest and should be further investigated in the future.

Taken together, these results suggest that at least for this class of permanent changes, inflation processes follow a diffusion on both the goods and spatial dimensions. Whether this is true for transitory monetary shocks is unknown and left for future research.

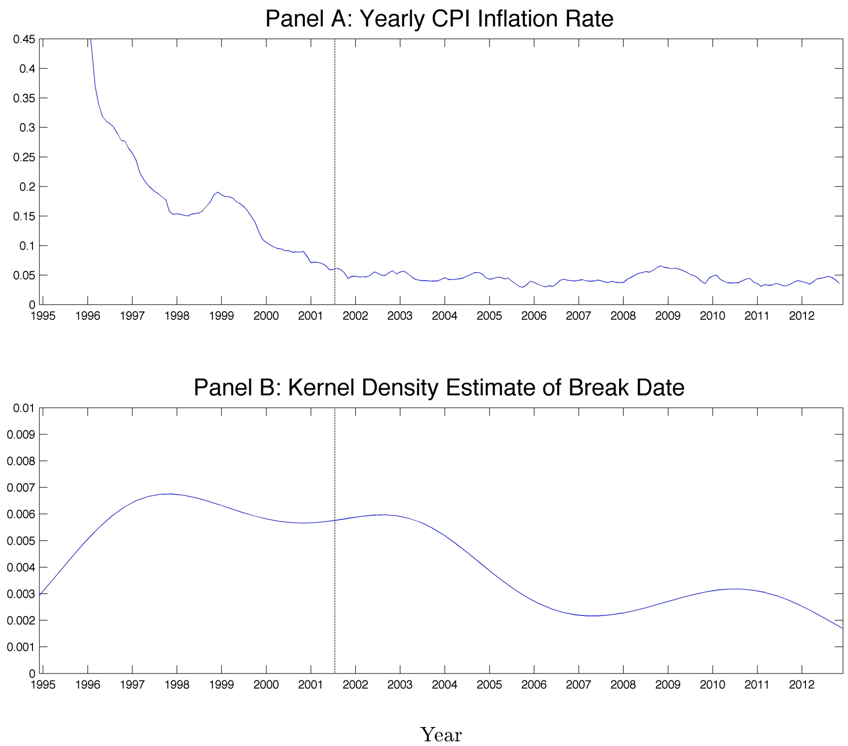

Figure 1: Panel A plots yearly CPI inflation rate along with the estimated break date (vertical, dotted line). Panel B plots a normal kernel density estimate for all good-city couples, conditional on experiencing at least one structural break. See Section 3.

The fact that inflation follows a diffusion process at the most disaggregated process matters for the design of optimal monetary policy. One well known fact is that spatial processes are characterized by a spatial multiplier that magnify individual shocks at the aggregate level. A corollary is that the design of optimal monetary policy might be improved by taking into account spatial dependencies that may affect the short or long-term price-level target, or the duration of the short-term deviation from a transitory shock.

This paper touches upon several important themes in monetary economics and several recent papers have pursued related objectives. There is now a well-established literature on the microeconomic evidence on the frequency of price changes showing that, contrary to standard rigid-price models, there is considerable flexibility in price changes at the micro-data level.[4] The interest here lies on whether the assumption of sluggish adjustment or price rigidity used in New Keynesian monetary models has any empirical support. Disaggregated CPI data has also been used to test other assumptions or results in international monetary theory, such as the law of one price or the Balassa-Samuelson effect.[5] A different strand of the literature seeks to improve the ability to forecast aggregate inflation using microeconomic data.[6] To best of my knowledge this is the first paper to study the heterogeneous response of different goods and services at the micro level after the implementation of an inflation targeting regime and to use it to investigate some of the determinants of structural change in persistence.

This paper is organized as follows. In the next section I describe the data used in the analysis of Section (3) where I describe the econometric test used to estimate the likelihood and timing of structural break and estimate their corresponding determinants. The last section discusses my results and concludes.

[4] A recent, up to date review of the literature can be found in Nakamura and Steinsson (2013). For the specific case of Mexico see Gagnon (2009), Ysusi (2009) and Ysusi (2010).

[5] See Crucini and Shintani (2008) and Hernández Vega (2012), respectively.

[6] See, for example, Duarte and Rua (2007) and Ibarra (2012).

2 Data

The main input in this paper is Mexican monthly CPI micro-data for the period January 1995 - December 2012. Since aggregate CPI inflation experienced a break around 2001 (Figure 1) it is convenient to use the same time period to explore the characteristics of the process of structural break at the more disaggregated level. The data includes price indexes for 283 categories for each of the 46 cities that are periodically surveyed to construct the Mexican CPI by the INEGI. Each of these 283 goods and services categories generally aggregate similar items and except for very specific cases cannot be considered purely homogenous goods. In what follows I will denote by g and c each of the corresponding goods and services categories and cities, and for convenience I will refer to the former as *goods* or *goods and services* indistinctly, but the reader should bear in mind that these also include services.

Spatially the data is collected from different establishments across forty-six cities in the country. One may group these using the thirty two states or two regional classifications that vary between four and seven regions.[7]

To present results I will use two alternative classifications for all goods: (i) the *expenditure* classification groups goods into 8 different categories that correspond roughly to an aggregate household budget. The categories are: *Food, Beverage and Tobacco*, *Apparel, Footwear and Accessories*, *Housing*, *Furniture and other Household Goods*, *Medical and Personal Care*, *Transport*, *Education and Entertainment* and *Other Goods and Services*; (ii) the standard core/non-core classification used by the INEGI to construct measures of core and non-core inflation. To compute core inflation using the definition used by

[7] The four geographical regions are: *North* that includes the states of Baja California, Sonora, Chihuahua, Coahuila, Nuevo León and Tamaulipas. *Central North* including Aguascalientes, Baja California Sur, Colima, Durango, Jalisco, Michoacán, Nayarit, San Luis Potosí, Sinaloa and Zacatecas. The *Central* region includes Mexico City, State of Mexico, Guanajuato, Hidalgo, Morelos, Puebla, Querétaro and Tlaxcala; the *South* includes Campeche, Chiapas, Guerrero, Oaxaca, Quintana Roo, Tabasco, Veracruz and Yucatán.

the Bank of Mexico one excludes from the aggregate CPI calculation the goods in the agricultural, concerted or administered and education subindexes.[8] Table (1) presents descriptive statistics using these categories for yearly and monthly inflation as well as for the CPI weights used to compute the aggregate index (Equation 1):

$$CPI_t = \sum_{c,g} \omega_{g,c} PI_{g,c,t} \quad (1)$$

Using the expenditure classification, the larger group is the one corresponding to Food, Beverage and Tobacco with 38.2% of all goods and services. In terms of the core/non-core classification, 82% of all goods and services are part of the core component (Columns 2 and 3). Excluding missing values, out of 216 monthly price index observations the average sample size is between 164 monthly observations (13.58 years) for the housing category (Column 5) and 199 monthly observations for several categories.

[8] Torres García (2003) presents a thorough discussion and description of several alternative core inflation definitions.

Table 1: Descriptive Statistics: Expenditure Groups

Panel A: Expenditure Classification of Goods and Services

	Goods and Services		**Total Observations**		**Inflation (%)**			**CPI Weights (%)**			
	Number	Share (%)	Sum	Average	Mean	Min	Max	Mean	Min	Max	Total Group
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Food, Beverage and Tobacco	108	38.2	990222	199.3	10	-20.8	88.3	0.005	0	0.533	23.0
Apparel, footwear and accessories	31	11	283930	199.1	7.9	-9.9	55.5	0.005	0	0.574	6.5
Housing	12	4.2	90444	163.8	5.9	-8.8	40.9	0.051	0	5.03	27.8
Furniture and HH Goods	41	14.5	365192	193.6	7.6	-16.8	67.8	0.002	0	0.178	4.0
Medical and Personal Care	38	13.4	327098	187.1	8.9	-12.2	63.6	0.004	0	0.168	7.7
Transport	21	7.4	188104	194.7	8.1	-11.2	58.7	0.016	0	0.908	14.3
Education and Entertainment	27	9.5	247194	199.0	8	-10.5	57.8	0.007	0	0.49	9.00
Other G&S	5	1.8	42920	186.6	7.7	-7.7	44.9	0.034	0	1.536	7.70
Core	231	81.6	2052818	193.2	8.4	-13.2	63.7	0.007	0	5.03	78.00
Non-Core	52	18.4	482286	201.6	10.5	-25.1	101	0.009	0	0.908	22.00
All Goods	283	100.0	2591592	194.3	8.8	-15.5	70.9	0.008	0	5.03	100

Panel B: Core-NonCore Classification of Goods and Services

	Goods and Services		**Total Observations**		**Inflation (%)**			**CPI Weights (%)**			
	Number	Share (%)	Sum	Average	Mean	Min	Max	Mean	Min	Max	Total Group
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Core: Goods											
Food, Beverage and Tobacco	68	24	609254	194.8	9.5	-15.2	71.9	0.005	0	0.414	14.6
Non-Food Merchandise	115	40.6	1032874	195.3	8.3	-14	67	0.004	0	0.715	19.4
Core: Services											
Housing	4	1.4	34084	185.2	6.9	-8.1	43.5	0.102	0	5.03	18.5
Education	8	2.8	77042	209.4	9.4	-8.3	47.4	0.014	0	0.49	5.1
Other Services	34	12	289720	185.2	6.5	-9.1	43.9	0.013	0	1.536	19.6
Non-Core: Agricultural											
Fruit and Vegetables	32	11.3	305288	207.4	11.4	-34.2	129	0.002	0	0.178	3.60
Livestock	8	2.8	75680	205.7	9.2	-14.6	65.3	0.013	0	0.533	4.80
Non-Core: Other											
Energy	5	1.8	36740	159.7	9.1	-6.2	49.8	0.041	0	0.773	9.4
Government Approved Fares	9	3.2	74422	179.8	7.6	-8.4	47	0.014	0	0.908	5.01

Notes: Table presents descriptive statistics for goods classified using expenditure, core and non-core inflation categories. Columns 1-2 provide information on the number of goods in each category with the corresponding share in the total. Columns 3-4 presents total and average number of usable observations for all goods within each category across all cities, Columns 5-7 provide average, maximum and minimum yearly and monthly inflation across all cities and goods in each category. Columns 8-11 present the mean, minimum, maximum and group CPI weights for all goods and cities (g, c) in each category.

Average yearly inflation was highest for goods in the non-core component and smallest for those in the housing category, and the range was also largest for non-core goods.[9] Finally, the last four columns present descriptive statistics for CPI average weights which will play a role later in the analysis. Note first that at the city level there are goods and services with zero weight in the CPI. Also, the maximum is given to Own Housing in Mexico City, and is in the order of 5%. The last column includes the aggregate weight given to each category of goods and services. Core goods represent 78% of the average expenditure of Mexican households with Non-food Merchandise and Other Services having the largest shares.

These CPI weights are estimated using expenditure data from the 2008 income and expenditure household Mexican survey (ENIGH) in the 46 municipalities included and correspond to the 2010 base in CPI calculation.[10] To understand the results that follow I have expressed the weights in percentage points, and to get an idea of the order of magnitudes Table (2) shows sample quantiles and other descriptive statistics.[11]

Table 2: Descriptive Statistics for Rescaled Weights

Percentiles					**Statistics**		
10%	25%	50%	75%	90%	Average	Min	Max
0.0001	0.0005	0.0014	0.0042	0.0127	0.0077	0	5.0297

Notes: Each column presents percentiles, average, minimum and maximum rescaled CPI weights (%) using the latest 2010 base.

[9] Since the Mexican economy was in a disinflationary period at beginning of my sample, the minimum inflation rates are all on the negative side.

[10] A thorough description can be found in Instituto Nacional de Estadística y Geografía (2011).

[11] The largest weight is given to the *Own Housing* (“vivienda propia”) in Mexico City.

3 Trend Stationarity and Structural Breaks

As explained in the Introduction, my aim is to test for non-stationarity (persistence) against the alternative of trend-stationarity with multiple breaks. I will follow Kapetanios (2005) who proposed the following model:

$$\pi_{g,c,t} = \mu_0 + \mu_1 t + \rho \pi_{g,c,t-1} + \sum_{i=1}^{k} \gamma_i \Delta \pi_{g,c,t-i} + \sum_{i=1}^{Smax} \phi_i DU_{i,g,c,t} + \sum_{i=1}^{Smax} \psi_i DT_{i,g,c,t} + \epsilon_{g,c,t} \quad (2)$$

where $\pi_{g,c,t}$ is yearly inflation at time t for good g at city c, $\mu_0 + \mu_1 t$ denotes the trend function, and $DU_{i,g,c,t} = 1(t > T_{b,i,g,c})$ and $DT_{i,g,c,t} = 1(t > T_{b,i,g,c})(t - T_{b,i,g,c})$ denote structural breaks in the mean and trend, respectively, with $T_{b,i,g,c}$ the i-th ($i = 1, \cdots, Smax$) structural break date for good g and city c. As is usual in Augmented Dickey-Fuller tests, the above specification includes k lags of differenced necessary for the disturbance $\epsilon_{g,c,t}$ to be white noise.

The null hypothesis of the test is $H_0 : \rho = 1, \mu_1 = \phi_1 = \cdots = \phi_{Smax} = \psi_1 = \cdots = \psi_{Smax} = 0$, and for any number of breaks $m \leq Smax$ the alternative hypotheses are of trend-stationarity with breaks, i.e. $H_m : \rho < 1$. The test statistic proposed by Kapetanios (2005) is the minimum t-statistic for ρ over all possible sample partitions with up to m structural breaks, i.e. $\tau^m_{min} = \min\{\tau^1, \tau^2, \cdots, \tau^m\}$ and τ^i is the t-statistic that minimizes the sum of squared residuals in the estimation of Equation (2) for up to i structural breaks. Starting with one break the process evolves recursively by partitioning the sample in up to $m+1$ subsets. Kapetanios (2005) provides critical values for τ^m_{min} at the 10%, 5%, 2.5% and 1% significance levels for $m = 1, \cdots, 5$ and three different specifications of breaks in the trend function: in Model A, he assumes that both the null and the alternative hypothesis have $\psi_1 = \cdots = \psi_{Smax} = 0$, i.e. he restricts the analysis to changes in the mean. Model B allows only for changes in the slope of the trend function, i.e. $\phi_1 = \cdots = \phi_{Smax} = 0$ and Model C allows for a general change in the trend function as expressed in Equation (2). In what follows I will only consider this last, more general alternative.

Before presenting the results several remarks about the implementation of the test are in order. First, I allow for a maximum of ten structural breaks, i.e. $Smax = 10$. Since simulated critical values in Kapetanios (2005) only allow for up to five structural breaks I extended the simulation in his paper to allow for up to ten breaks.[12] The critical values used are presented in Table (A1) in Appendix A.

Second, before conducting the tests I also test for the joint presence of monthly seasonality. If I cannot reject the null of seasonality using a conventional F-test I use the residuals from this estimation, otherwise I use the original time series.[13] Third, in what follows I fix a significance threshold of 10%.

Finally, it is well known that the choice of the number of lags (k) in augmented Dickey-Fuller tests may distort the size and power of the test (Ng and Perron (1995)). Since I estimated up to $Smax = 10$ structural breaks for all the (g, c) combinations, using standard information criteria would have been computationally demanding. For this reason I selected several (g, c) cases and generally found that the AIC and BIC were monotonically decreasing for up to $k = 15$ lags; plotting the information criteria as a function of k I found a large discontinuity at $k = 12$ lags, so in what follows I fix k to 12 lags.

Table (3) summarizes the results using both of the classifications described in the

[12]The choice of ten structural breaks is rather arbitrary. It will be seen below that results do not change if a lower upper bound was imposed, since most disaggregated price indexes experienced less than three breaks and the distribution is heavily concentrated on one and two breaks.

[13]As discussed in Kapetanios (2005), since the asymptotic distribution is not free of nuisance parameters I decided to prefilter each time series for monthly seasonality. Nonetheless I have also simulated corresponding critical values allowing for monthly seasonality under the alternative and the results remain the same.

previous section. For each category, the second ($I(1)$) and third columns give the fraction of goods for which the test cannot reject the null and their corresponding aggregated CPI weight, respectively, even after allowing for up to $Smax = 10$ structural breaks. The next column provides information on the average estimated autoregressive parameter $\hat{\rho}(m)$ where m is the minimum number of breaks necessary to achieve stationarity if $m \leq Smax$ or for the case of no breaks whenever I cannot reject the null hypothesis of a unit root. Conditional on being trend-stationary with breaks, the next ten columns provide frequencies for each number of breaks. Finally, the last five columns provide summary statistics of the estimated date of structural break using the mean, the median, the maximum and minimum and the standard deviation (in months).

Starting with Panel A, for almost 20% of all (g, c) couples I cannot reject the null of a unit root even after allowing for up to ten breaks in the trend function. In the construction of CPI, these non-stationary cases represent 15% of the total weight, computed as the sum of the CPI weights across the corresponding city-goods cases. Inflation for goods and services in the Housing, Transport and Education categories is generally less likely to be persistent, consistent with the finding that goods in the core classification are generally more persistent than those in the non-core classification. Among the core goods, 21% appear to be non-stationary, representing less than 13% of the total CPI share; 14% of non-core goods are classified as non-stationary, representing less than 3% of all cases.[14]

Turning now to the trend-stationary subset of (g, c) couples, columns 4-5 show that in the vast majority of cases one or two breaks in the trend are sufficient to obtain stationarity, and one break is enough for almost 80% of all cases. Consistent with the previous finding, stationary non-core goods are more likely to achieve stationarity after only one change.

The last five columns provide descriptive statistics on the distribution of estimated

[14]Since non-core goods are relatively more volatile this result may appear to be counterintuitive. In the next section I will further explore and test the validity of this finding.

break dates. First, this distribution is not symmetric: in general, the average break date takes about a year more than the median break date, the latter being closer to the estimated break for yearly data. This finding suggests an answer to one of the questions posed in the introduction: while CPI is an average of disaggregated prices, the break in aggregate inflation is closer to the median break than to the average break. The earlier break dates are found at the beginning of 1996, and the later were estimated in the first half of 2012. Moreover, the distribution exhibits considerable variation: conditional on experiencing a break the estimated standard deviation in the break is around 60 months (last column). To understand this large standard deviation, it is instructive to remember that the distribution is multimodal (Figure 1).

A complementary picture is obtained by focusing on the actual core/non-core classification in Panel B. Within the core classification, goods are slightly more persistent than services, the main difference explained by the Education subgroup.

The non-core goods and services are generally less persistent, with the exception of the eight (Table 1) Livestock goods. Moreover, I can reject the null of a unit root for all of the 5 goods within the Energy subgroup, for which the distribution of changes is the tightest of all with an estimated standard deviation of only 10 months. This result should not come as a surprise given the regulated nature of goods within this category.[15]

[15] The five goods are electricity, gas (2 additional categories), and gasoline (2 additional categories).

Table 3: Trend-Stationarity vs. Non-Stationarity

Panel A: Expenditure Groups

Group	$I(1)$	CPI Weight	$\widehat{E(\hat\rho)}$	Number of Breaks in Trend: $m=1$	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$	$m=7$	$m=8$	$m=9$	$m=10$	$\widehat{E(\hat T_b)}$	$\widehat{Med(\hat T_b)}$	$\widehat{Min(\hat T_b)}$	$\widehat{Max(\hat T_b)}$	$\widehat{SD(\hat T_b)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Food, Beverage and Tobacco	0.203	0.0551	0.648	0.852	0.052	0.025	0.021	0.016	0.01	0.008	0.006	0.005	0.005	Jan-03	Feb-02	Feb-96	Dec-11	56.129
Apparel, footwear and accessories	0.213	0.0107	0.729	0.734	0.098	0.051	0.036	0.028	0.018	0.014	0.006	0.008	0.005	Nov-01	Dec-00	Mar-96	Dec-11	48.116
Housing	0.101	0.0152	0.677	0.861	0.061	0.036	0.012	0.009	0	0.006	0.006	0.009	0	Apr-02	Nov-00	May-96	Dec-11	57.708
Furniture and HH Goods	0.244	0.0076	0.711	0.781	0.072	0.041	0.038	0.018	0.009	0.008	0.011	0.012	0.01	Oct-03	Jan-03	Mar-96	Dec-11	53.636
Medical and Personal Care	0.203	0.0114	0.703	0.765	0.083	0.042	0.037	0.021	0.014	0.013	0.007	0.007	0.009	Sep-03	Jan-03	Mar-96	Mar-12	57.05
Transport	0.149	0.0095	0.696	0.771	0.102	0.041	0.015	0.019	0.023	0.005	0.01	0.008	0.006	Nov-03	Aug-03	Feb-96	Jan-12	49.436
Education and Entertainment	0.168	0.0179	0.636	0.662	0.108	0.078	0.044	0.037	0.02	0.017	0.018	0.011	0.004	Aug-02	Oct-01	May-96	Mar-12	52.343
Other G&S	0.219	0.0243	0.142	0.73	0.096	0.045	0.022	0.039	0.011	0.028	0	0.011	0.017	Jan-02	Mar-01	Aug-96	Dec-11	44.285
Core	0.212	0.1257	0.699	0.77	0.079	0.044	0.032	0.023	0.014	0.011	0.009	0.009	0.007	Feb-03	Feb-02	Feb-96	Mar-12	55.599
Non-Core	0.14	0.0265	0.526	0.874	0.056	0.02	0.015	0.01	0.009	0.006	0.005	0.004	0.002	Dec-02	Feb-02	Jul-96	Jan-12	49.566
All Goods	0.199	0.1522	0.668	0.79	0.074	0.04	0.029	0.021	0.013	0.01	0.009	0.008	0.006	Jan-03	Feb-02	Feb-96	Mar-12	54.504

Panel B: Core/Non-Core Groups

Group	$I(1)$	CPI Weight	$\widehat{E(\hat\rho)}$	Number of Breaks in Trend: $m=1$	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$	$m=7$	$m=8$	$m=9$	$m=10$	$\widehat{E(\hat T_b)}$	$\widehat{Med(\hat T_b)}$	$\widehat{Min(\hat T_b)}$	$\widehat{Max(\hat T_b)}$	$\widehat{SD(\hat T_b)}$
Core: Goods																		
Food, Beverage and Tobacco	0.231	0.03	0.74	0.813	0.063	0.034	0.025	0.021	0.013	0.01	0.008	0.007	0.006	Mar-03	Feb-02	Feb-96	Dec-11	59.292
Non-Food Merchandise	0.216	0.028	0.721	0.783	0.073	0.041	0.034	0.022	0.013	0.011	0.008	0.009	0.007	May-03	Jul-02	Mar-96	Mar-12	55.173
Core: Services																		
Housing	0.19	0.014	0.743	0.805	0.087	0.034	0.02	0.013	0	0.013	0.013	0.013	0	Nov-03	May-03	May-96	Dec-11	50.877
Education	0.065	0.010	0.559	0.48	0.157	0.16	0.064	0.052	0.035	0.023	0.015	0.009	0.006	Sep-01	Jun-01	May-96	Mar-12	44.97
Other Services	0.201	0.036	0.568	0.725	0.107	0.048	0.032	0.026	0.015	0.012	0.015	0.009	0.012	Apr-02	Mar-01	Feb-96	Dec-11	51.226
Non-Core: Agricultural																		
Fruit and Vegetables	0.109	0.003	0.439	0.93	0.03	0.01	0.013	0.006	0.002	0.003	0.003	0.002	0.001	Sep-02	Jun-01	Nov-96	Dec-11	49.414
Livestock	0.36	0.021	0.751	0.786	0.063	0.024	0.024	0.029	0.029	0.019	0.01	0	0.015	Dec-02	Oct-01	Jul-96	Dec-11	58.893
Non-Core: Other																		
Energy	0	0	0.694	0.967	0	0.022	0	0	0.011	0	0	0	0	Sep-03	Oct-03	Aug-98	Jul-04	9.323
Government Approved Fares	0.127	0.005	0.65	0.683	0.161	0.053	0.022	0.022	0.031	0.006	0.009	0.012	0	Aug-03	Jun-02	Jul-96	Jan-12	52.031

Notes: For each group, Column (2) reports the fraction of goods and services that remain non-stationary after allowing for a fixed number of maximum structural breaks of $m = 10$ using the test in Kapetanios (2005) and Column (3) the total CPI weight for those goods that are non-stationary. Column (4) report the average estimated ρ in Equation (2) corresponding to the rejection of the null hypothesis. Columns 4-13 report the fraction of goods and services for which the estimated number of breaks is equal to $m = 1, \cdots, 10$ conditional on achieving stationarity. The last five columns report descriptive statistics for the estimated break date. For the case of more than one break these columns report the date corresponding to the rejection of the null hypothesis.

I will now go further in this analysis and try to understand some of the determinants of the timing and likelihood of a break using regression analysis. To motivate the analysis that follows, suppose that structural breaks across the (g, c) dimensions follow a diffusion process, i.e. once a specific couple experiences a break its "neighbors" are more likely to experience it too. While spatial diffusion can be approximated by some distance function using geographical coordinates— say, the Euclidean distance between cities[16]— there is no straightforward measure of proximity on the goods space. To tackle this problem I use two alternative procedures: first, I include group fixed effects according to any of the two classifications described in the previous section.[17] Moreover, I also exploit the distribution of CPI weights across goods and services by including linear and quadratic terms of each corresponding weight.

Specifically, I will now estimate regression models for the estimated likelihood and timing of a break, expressed as functions of corresponding CPI weights and the occurrence and timing of past breaks in neighboring cities, as well as group and cities fixed effects:

$$
\begin{aligned}
tb_{g,c} &= \alpha_0 + \alpha_1\omega_{g,c} + \alpha_2\omega_{g,c}^2 + \rho_s \sum_{c'\neq c} \tilde{d}_{g,c,c'} tb_{g,c'} + X'_{g,c}\beta_{tb} + \epsilon_{g,c} \quad (3)\\
\mathbf{1}[\hat{\rho} < 1|s = 10\%]_{g,c} &= \gamma_0 + \gamma_1\omega_{g,c} + \gamma_2\omega_{g,c}^2 + \rho_s \sum_{c'\neq c} \tilde{d}_{g,c,c'} \mathbf{1}[\hat{\rho} < 1|s = 10\%]_{g,c'} \\
&\quad + X'_{g,c}\beta_{ur} + \eta_{g,c} \quad (4)
\end{aligned}
$$

where the dependent variables are the natural logarithm of the estimated date for a change in persistence for all goods-cities couples where a positive break was found $(tb_{g,c})$

[16]The Euclidean distance is computed using the median geographical coordinate for each city.

[17]I only report the results for the second, core-noncore classification. Results using the remaining fixed effects are similar and are available from the author upon request.

and $\mathbf{1}[\hat{\rho} < 1|s = 10\%]_{g,c}$ is an indicator variable that takes the value one if I can reject the null hypothesis of a unit root for couple (g, c) both using a 10% significance level threshold. Moreover, $\omega_{g,c}$ denotes each CPI weight (Equation 1), X includes a full set of group and city fixed effects and to capture any degree of spatial correlation (ρ_s) I also include the weighted average of each dependent variable across all neighboring cities, where $\tilde{d}_{g,c,c'}$ denote the normalized reciprocal Euclidean distance between cities c and c' using the actual coordinates for all cities.[18]

Several remarks follow. First, since I have estimated up to ten structural breaks it is unclear which date should be assigned to the actual break. In the results that follow I will consider only those cases where I have estimated one structural break, i.e. all other cases are classified as non-stationary. In Table (B1), Appendix B, I report the results where I use the information on the ten structural breaks, and I assign the date of the last break needed to achieve stationarity. It is shown that results are robust to this potential source of misspecification, explained by the fact that the distribution of the number of the breaks is heavily concentrated on the first two breaks.[19]

Second, I estimate two different models using Equation (3): Model A uses only the sample of (g, c) couples where I estimated a positive date of change, i.e. those couples that are trend-stationary with breaks and the time of break is assumed to be lognormally distributed. In Model B I extend the analysis to the full sample of (g, c) couples and estimate a normal Tobit censored model, where, by assumption the possibly unobserved (log) time of change is $tb^*_{g,c} = \min\left\{tb_{g,c}, \bar{t}\right\}$ and $\bar{t}$ corresponds to the (log) date of the last

[18] While there is some socioeconomic data at the city level that could in principle be used to control for other unobserved city effects, it is usually available for only one time period or for time periods that need not coincide with the timing of events used here. For this reason I am forced to used city fixed effects and assume away any time varying city effects that may explain some of the results.

[19] Importantly, breaks are not chronologically ordered, so it does not generally follow that whenever there are more than one structural break the estimated date takes place later than the first break, i.e. a priori this does not impose any form on the distribution of break dates.

observation in our sample, i.e. December 2012.[20] Using the second equation I estimate a linear probability model for the likelihood of experiencing a break.

Regarding the spatial autoregressive term, note first that closer cities have a stronger effect on the average since the weights are (normalized) reciprocal distances. Second, the spatial correlation coefficient ρ_s is not to be confused with the corresponding first-order autoregressive parameter used in the tests above. Third, as discussed in the motivating paragraphs I seek to estimate a spatial diffusion process, i.e. the causal effect that neighboring cities have on each outcome. To attain this I follow the time series definition of causality and take the weighted average only across those (g, c) couples that experienced a break in the past. Notice that if $\rho_s = 0$ there is no correlation on the spatial dimension, e.g. because all (g, c) couples experience a common shock. Whenever $\rho_s > 0$ there is suggestive evidence that the timing of a break follows a diffusion process on the spatial dimension; finally, the case of negative spatial correlation is harder to interpret, since for each (g, c) couple, a later average neighboring break date would imply and earlier break for that couple— implying spatial co-movement; alternatively, an earlier average neighboring break date implies spatial disentanglement.

Because of the large number of controls, I present the results in separate tables. Results for the CPI weights and spatial determinants are presented in Table (4). Using the restricted sample (Panel A), I first find that conditional on experiencing a break, the timing of breaks for different cities is negatively correlated. As discussed above, the case of negative spatial correlation is hard to interpret, but a literal interpretation is that, for a fixed radius, goods and services in cities within this radius we find both early and late break dates, conditional on breaks taking place. Interestingly, I also find a monotone and

[20]Under a normality assumption for Model A (i.e. duration to a change in persistence is lognormally distributed) Model B clearly nests Model A. Since I am not interested in estimating the marginal effect of the regressors on the hazard function but only on the effect they have on the duration of change in persistence this is not a problematic assumption (Wooldridge (2010)).

concave relation between the timing of a break and CPI weights, i.e. conditional on experiencing a break, goods that are relatively more important in the average household's budget experienced a break later. The fact that the relationship is concave implies that the process of structural break is not unbounded, with a maximum around weights close to 3%.

Consistent with the hypothesis of a spatial diffusion process, when I use the full sample of (g, c) couples (Panels B and C) I find strong and positive correlation, both for the timing and likelihood of a break. Moreover, I find that couples with higher CPI weights were more likely to experience a break (Panel C) and this relationship is also concave. The same result holds for the Tobit model (Panel B) once I include city fixed effects.

Before going on it is worth expanding on these findings. First, comparing results in Panel A and B it is clear that constraining the sample has an important effect on the spatial autocorrelation estimate. The fact that the likelihood of a break follows a diffusion process (Panel C) helps understand these dissimilar results: if one specific (g, c) couple is more likely to experience a break if other couples in proximate cities have already experienced a break one should expect to have the timing of the breaks to also be positively correlated. Interestingly, under this interpretation the causation is through the likelihood which then implies correlation of the timing of the breaks. This shows the advantage of modeling the break date as a latent variable— as opposed to restricting the sample to those couples that have already a break.

It is also worthwhile speculating about the causes behind the estimated relationship between CPI weights and the dependent variables. First, as Bénabou (1992) and Chirinko and Fazzari (2000) have found, inflation and market power have been found to be positively correlated, a result consistent with the view that, as inflation increases, households are more willing to exert effort searching for cheaper alternatives, potentially increasing the the degree of competition in industries with preexisting market power. As Figure 1 shows, the case of Mexico's structural break considered here is one of a general movement to a lower inflation, less persistent regime. By extending the previous observation one may argue that, with lower general inflation, households will exert higher search effort precisely on those goods (and cities) that are relatively more important in their budget, making it more likely to experience a break towards the low and stable-inflation regime. The corresponding results obtained in Panel A would then be a case of sample selection.

Turning now to the group-fixed effects, and moving from right to left in Table (5) it is interesting that *relative* to the excluded reference group Beverage, Food and Tobacco, only the Education subgroup appears to be more likely to have experienced a break. Moreover, as shown in the last row, while relative to the non-core category those (g, c) couples in the core classification are less likely to have experienced a break, this difference is not statistically significant. Recall that Table (3) showed that a larger fraction of goods in the core classification had not experienced a structural break, a result that appears to contradict the finding that goods in the non-core category are more susceptible of experiencing transitory shocks that make them more volatile.[21] The result in Table (5) shows that the difference is not significant once we control for spatial effects, for CPI weights and city fixed effects.

[21] To be sure, there need not be a contradiction if higher volatility is the result of the higher variance of weakly stationary time series. Nonetheless, a non-stationary time series with time-dependent variance will appear to be more volatile, as in the case of an $AR(1)$ unit root process.

Table 4: CPI Weights and Spatial Autoregressive Coefficient

	Panel A: Log Normal		
	(1)	(2)	(3)
SAR (ρ_s)	-0.293***	-0.322***	-0.321***
	(0.01)	(0.01)	(0.01)
CPI Weight (α_1)		0.547***	0.483***
		(0.18)	(0.18)
CPI Weight^2 (α_2)		-0.099***	-0.086**
		(0.04)	(0.04)
	Panel B: Tobit		
	(1)	(2)	(3)
SAR (ρ_s)	0.391***	0.486***	0.519***
	(0.01)	(0.01)	(0.01)
CPI Weight (α_1)		-0.335	1.427**
		(1.03)	(0.7)
CPI Weight^2 (α_2)		-1.917	-0.188
		(1.29)	(0.17)
	Panel C: Linear Probability		
	(1)	(2)	(3)
SAR (ρ_s)	0.25***	0.207***	0.209***
	(0.04)	(0.04)	(0.04)
CPI Weight (α_1)		0.398**	0.402**
		(0.15)	(0.17)
CPI Weight^2 (α_2)		-0.117**	-0.119*
		(0.06)	(0.06)
Group Fixed Effects	No	Yes	Yes
City Fixed Effects	No	No	Yes

Notes: Panel A, B and C display estimates for the log normal (restricted sample), censored normal (full sample) and linear probability models, respectively, using Equations (3)-(4) as explained in the text. Standard errors are in parenthesis with the following characteristics: in Panel A I report FGLS random effects at the city level standard errors; in Panel B I report the asymptotic covariance matrix and in Panel C FGLS standard errors corrected for heteroskedasticity.

In terms of the actual timing of the break, Panel B shows that controlling for city fixed effects generates considerable variation in the results. Taking this latter specification as the more general one, I find that Non-Food goods, Education services, Other Services and Energy and Government Approved Fares experienced an earlier break, while Housing services and non-core agricultural goods experienced a later break. It is also interesting to find that relative to non-core goods and services (last two rows), Core goods experienced a later break, even after controlling for each group fixed effect, spatial correlation and CPI weights. This result is consistent with the lower (though statistically insignificant) likelihood of experiencing a break found in Panel C.

Finally, restricting the attention to the subsample of (g, c) couples that have already experienced a break (Panel A), I find that relative to the reference group, Non-Food goods, Housing services and Energy experienced a later break, while Education and non-core agricultural goods experienced an earlier break, and these results are robust to a specification that include or exclude city fixed effects.

It is also interesting to check for significant city fixed effects, as they might say something about the general direction of the shocks in the diffusion process. Table (B4) in the Appendix presents the estimates and their corresponding standard errors, where the excluded reference city is Mexico City. In 89%, 56% and 100% of the cases, respectively for each model, there are no statistically significant differences in the timing or likelihood of experiencing a break with respect to the capital Mexico City. After controlling for all other factors, and using the results from the Tobit model, only 16% of the cities experienced a break *later* than Mexico City, and 29% of the cities experienced it earlier. This shows that there is no general diffusion pattern flowing from the center (and specifically, Mexico City) to the periphery.

Overall these results show the following picture: first, except for Educational services, most goods are equally likely to experience a break once I control for CPI weights, spatial effects and city fixed-effects. In terms of the timing of the breaks, I find that controlling for city fixed effects has an effect only when I consider the extended sample, i.e. it shows that there is considerable heterogeneity across states and groups, even after controlling for everything else. Moreover, this heterogeneity disappears once I restrict the analysis to the subsample of couples where a break has already been observed.

Table 5: Determinants of Trend-Stationarity: Group Fixed Effects

	Panel A: Log Normal		**Panel B: Tobit**		**Panel C: Lin.Prob**	
	(1)	(2)	(1)	(2)	(1)	(2)
Core: Goods						
Non-Food	0.047***	0.047***	0.165***	-0.418***	0.005	0.005
	(0.01)	(0.01)	(0.04)	(0.05)	(0.01)	(0.01)
Core: Services						
Housing	0.133***	0.14***	-1.077***	0.473***	-0.005	0.00
	(0.03)	(0.04)	(0.15)	(0.18)	(0.03)	(0.03)
Education	-0.051***	-0.051***	-0.383***	-1.16***	0.042**	0.043**
	(0.02)	(0.02)	(0.1)	(0.12)	(0.02)	(0.02)
Other Ss.	-0.022	-0.022	0.227***	-0.141***	-0.001	0.00
	(0.02)	(0.02)	(0.06)	(0.07)	(0.01)	(0.01)
Non-Core: Agricultural						
F&V	-0.048	-0.04	0.466	1.15***	0.007	0.017
	(0.12)	(0.12)	(0.31)	(0.35)	(0.07)	(0.07)
Livestock	-0.332***	-0.324***	-0.534*	1.174***	-0.019	-0.011
	(0.11)	(0.11)	(0.28)	(0.32)	(0.06)	(0.06)
Non-Core: Other						
Energy	0.942***	0.951***	-0.821**	-0.68*	-0.026	-0.01
	(0.13)	(0.13)	(0.33)	(0.38)	(0.07)	(0.07)
Government	0.005	0.014	-0.846***	-0.61*	-0.009	0.00
	(0.12)	(0.12)	(0.32)	(0.36)	(0.07)	(0.07)
Core (relative to Non-Core)						
Core	-0.174	-0.166	1.455***	2.722***	-0.015	-0.007
	(0.12)	(0.12)	(0.3)	(0.34)	(0.06)	(0.06)
N	9314	9314	13156	13156	13156	13156
City FE	No	Yes	No	Yes	No	Yes

Notes: Panel A, B and C display estimates for the log normal (restricted sample), censored normal (full sample) and linear probability models, respectively, using Equations (3)-(4) as explained in the text. Standard errors are in parenthesis with the following characteristics: in Panel A I report FGLS random effects at the city level standard errors; in Panel B I report the asymptotic covariance matrix and in Panel C FGLS standard errors corrected for heteroskedasticity. The excluded reference groups are Beverage, Food and Tobacco and the non-core groups. *F&V* denotes *Foods and Vegetables*, and *Ss* denotes services. In the State fixed effects specification I excluded México DF.

4 Discussion and Conclusion

My aim in this paper has been two-fold: first, by testing for multiple structural breaks in the trend function using micro-data price indexes I show that there is considerable heterogeneity in the timing and likelihood of a structural break. Second, I study the determinants of the timing and likelihood of a break and show that if our aim is to improve our understanding of price-setting dynamics one promising line of research is to use this microlevel variation.

Several findings emerge from this approach. First, I show that both the likelihood and the unrestricted timing of breaks display strong positive spatial autocorrelation, indicating that for any given city, what happens in neighboring cities is of direct importance. When I restrict the analysis to those cases where a break has already taken place I find that the timing is negatively correlated at the spatial level, suggesting that while spatial variation is important in explaining the global properties of the process, local conditions at the goods level may partly explain the actual observed timing.

While proximity on the spatial axis is easily measured, there is no objective distance function on the goods space that allows me to test for diffusion process on this dimension. The avenue explored here is to use variation across groups of goods and household expenditure, as measured by CPI weights. The general finding is that cases with higher weights were more likely to experience a break, and generally experienced the break later, relative to those with lower weights. Interestingly, this relationship is also generally concave, i.e. there are natural limits to the diffusion along this dimension.

Across groups, I find that only Education services were more likely to experience a break (relative to Food, Beverage and Tobacco) but there are some other systematic findings with the timing of events that suggest that the goods dimension also plays a role in the diffusion process.

Taken together these results suggest that this class of inflationary shocks follow a diffusion process across the geographical and goods space. Whether this is true for other shocks is uncertain and is part of a future research agenda that I discuss below. Before doing I will first discuss one important implication for the design of monetary policy, followed by a discussion of several potential drawbacks or shortcomings of the present analysis.

That spatial dependence of disaggregated price data may turn out to be relevant for the design of monetary policy can be seen from the well known fact that positive spatial dependence generates a multiplier that magnifies individual exogenous shocks at the aggregate level.[22] A simple two-goods example will serve to illustrate.

Suppose that the aggregate price index is a weighted average of the prices of two goods:

$$\begin{aligned} \overline{P} &= \lambda P_1 + (1-\lambda)P_2 \\ P_1 &= \alpha + \rho P_2 + \epsilon_1 \\ P_2 &= \alpha + \rho P_1 + \epsilon_2 \end{aligned}$$

Here α is taken to be a permanent (level) common effect, and the idiosyncratic shocks ϵ_i, $i = 1, 2$ correspond to transitory effects. By solving P_1 and P_2 in terms of the exogenous permanent and transitory effects and replacing these in the weighted average we obtain:

$$\overline{P} = \frac{\alpha}{1-\rho} + \epsilon_1 \left[\frac{\lambda + (1-\lambda)\rho}{1-\rho^2} \right] + \epsilon_2 \left[\frac{(1-\lambda) + \lambda\rho}{1-\rho^2} \right]$$

It is now easy to see that permanent and transitory effects are magnified whenever $\rho \in$

[22] On spatial multipliers see Anselin (2003). Similar effects have been found in the literature on social interactions and network effects. See e.g. Becker and Murphy (2000) or Glaeser and Scheinkman (2003).

$(0, 1)$. The corollary from this simple example is that taking into account the spatial dependence matters from the perspective of the optimal monetary response by a Central Bank.[23]

I now discuss several pitfalls from the methodology used. First, I consider only a very specific type of shock one that is not really well understood, i.e. shocks that are strong enough to generate a permanent break in the trend function of a stationary process. Nonetheless one can easily imagine diffusion processes with only transitory effects. While using the former has a clear advantage— permanent effects are more easily identifiable — the latter may not only be more frequent but may also provide a deeper insight into the price formation process.

Second, it is well known that OLS estimates of spatial autoregressive models are inconsistent (e.g. Ord (1975) or Arbia (2006)). In this paper I have avoided this problem by restricting the right-hand side spatial effect to all of those (g, c) cases that experienced a break *before* the corresponding left-hand side observation, forbidding the simultaneity problem that generates this type of inconsistency. Nonetheless, as a robustness check I have estimated Models A and C using Maximum Likelihood methods common in the spatial econometrics literature and results do not vary.[24]

Two additional sources of concern may arise by the use of a two-stage method where in a first stage I estimate the timing and likelihood of a structural break, and these are used as inputs in the second stage estimation of the determinants. First, one may argue against the use of fixed significance threshold and the robustness of the results to different choices (e.g. 10% against 5% or 1%). Second, the fact that the second stage uses estimates as dependent and independent variables may create inconsistencies due to measurement

[23]Using a simple dynamic generalization where the relation depends on lagged values of the other prices in the economy it can be easily shown that equilibrium steady-state values display this same positive spatial multiplying effect, but also that the duration of temporary shocks is affected.

[24]Results are available from the author upon request.

error.

Related to the latter, it is well known that the presence of additive measurement error in the dependent variable does not generate inconsistent estimates as long as the error is uncorrelated with the regressors. Here, however, the error comes from estimation, is not additive— it appears inside a nonlinear function— and since I estimate the spatial autocorrelation, it also appears as a regressor. Nonetheless, under certain standard regularity conditions, the estimated break date is a consistent estimator of the true, unobserved, break date so as the sample size (T) grows the measurement error disappears yielding consistent estimates.[25]

Related to the choice of a significance level the main tradeoff is between size and power. A lower significance threshold makes it harder to reject the null hypothesis of a unit root increasing the number of (g, c) cases that the test labels as non-stationary in Model C, reducing the sample of finite break dates in Model A and increasing the number of censored cases in Model B . It follows that a stricter choice of significance threshold (say, 1%) increases the probability of a Type II error and lowers the probability of a Type I error, so it is hard to evaluate the effects of this type of measurement error have on the estimates.

To illustrate this, Table (B2) presents the first-stage results using a 5% significance threshold. Several findings emerge: first, the fraction of goods found to be non-stationary almost doubles, reaching now 37.6% of all goods and services. Second, the distribution of the number of breaks becomes more evenly distributed, with up to six structural breaks needed for at least 90% of all (g, c) cases that experienced a break to attain stationarity. Third, the distribution of break dates becomes more concentrated at the beginning of the

[25] Strictly speaking, the estimated *fractions* $\lambda_m \in (0, 1)$ defined by $Tb_m = \lambda_m T$ are consistent estimates of the true unobserved fractions. See Bai and Perron (1998) that also allow for trending regressors. The method proposed by Kapetanios (2005) is a generalization of the methods proposed by Bai and Perron (1998).

sample, as Figure (2) shows. Interestingly, the signs of the second-stage estimated coefficient do not vary considerably using this restricted sample, but the linear and quadratic CPI weights effects are generally not significant (Table B3).

Fifth, as shown in Table (2), the distribution of CPI weights is positively skewed due to the relative large weights on some goods, possibly generating the highly significant monotone, concave relation found. Three robustness checks were performed: first I excluded up to the 30% largest weights. Second, for Model A I estimated least absolute deviation (LAD) model.[26] Finally, I excluded Mexico City from the analysis. As can be seen in Table C1 in Appendix C qualitatively my results do not change, showing that my results are not driven by outlying observations.

I finally discuss potential avenues for future research. First, as this paper has shown, exploiting the microlevel data variability may yield interesting insights into the price-setting behavior in an economy. Here I have focused only on the persistence of the inflation processes but one may wish to study the systematic differences in seasonality and even in the relative magnitude of estimates of persistence. One may also wish to study more directly the differential effect that monetary policy has at the goods and services and city levels.

[26] Models A and C were estimated by FGLS but a LAD estimator cannot be used with the linear probability model.

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Appendix A Critical Values used in Section (3)

Table A1: Critical Values for Tests of Up To 10 Structural Breaks

$Smax$	1%	5%	10%
1	-5.450	-4.966	-4.698
2	-6.555	-6.005	-5.672
3	-7.299	-6.878	-6.559
4	-8.096	-7.590	-7.279
5	-8.909	-8.294	-7.962
6	-9.530	-8.852	-8.547
7	-10.155	-9.511	-9.177
8	-10.655	-9.997	-9.712
9	-11.234	-10.569	-10.146
10	-11.730	-11.016	-10.574

Notes: Table presents simulated critical values corresponding to Model C in Kapetanios (2005) for up to $Smax = 10$ structural breaks. Simulation was conducted in Matlab using trimming parameter of the sample equal to 0.05, 1000 simulations of standard random walks with standard normal errors of size $N = 250$ as in the original simulations.

Appendix B Additional Results

Table B1: Robustness: Results for up to 10 structural breaks

	Panel A: Log Normal		
	(1)	(2)	(3)
SAR (ρ_s)	-0.365***	-0.382***	-0.382***
	(0.01)	(0.01)	(0.01)
CPI Weight (α_1)		0.415**	0.318*
		(0.18)	(0.18)
CPI Weight^2 (α_2)		-0.068*	-0.005
		(0.03)	(0.04)
R^2	0.56	0.6	0.6
N	9462	9314	9314
	Panel B: Tobit		
	(1)	(2)	(3)
SAR (ρ_s)	0.153***	0.372***	0.057***
	(0.01)	(0.01)	(0.01)
CPI Weight (α_1)		1.125	-0.142
		(0.93)	(0.73)
CPI Weight^2 (α_2)		-1.523	1.218***
		(1.05)	(0.17)
Loglikeli	-23661.07	-24253.11	-25717.59
N	13156	12972	12972
	Panel C: Linear Probability		
	(1)	(2)	(3)
SAR (ρ_s)	0.177***	0.164***	0.167***
	(0.04)	(0.04)	(0.04)
CPI Weight (γ_1)		0.379***	0.235*
		(0.13)	(0.14)
CPI Weight^2 (γ_2)		-0.11***	-0.086
		(0.03)	(0.03)
N	13156	12972	2972
Group Fixed Effects	No	Yes	Yes
State Fixed Effects	No	No	Yes

Notes: Panel A, B and C display estimates for the log normal (restricted sample), censored normal (full sample) and linear probability models, respectively, using Equations (3)-(4) as explained in the text. Standard errors are in parenthesis with the following characteristics: in Panel A I report FGLS random effects at the city level standard errors; in Panel B I report the asymptotic covariance matrix and in Panel C FGLS standard errors corrected for heteroskedasticity.

Table B2: Results for 5% Significance Level

Panel A: Expenditure Groups

Group	$I(1)$	CPI Weight	$\widehat{E(\hat{\rho})}$	Number of Breaks in Trend $m=1$	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$	$m=7$	$m=8$	$m=9$	$m=10$	$\widehat{E(\hat{T}_b)}$	$\widehat{Med(\hat{T}_b)}$	$\widehat{Min(\hat{T}_b)}$	$\widehat{Max(\hat{T}_b)}$	$\widehat{SD(\hat{T}_b)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Food, Beverage and Tobacco	0.354	0.0993	0.738	0.522	0.107	0.112	0.075	0.042	0.044	0.034	0.033	0.02	0.012	May-01	Mar-00	Feb-96	Oct-11	47.034
Apparel, footwear and accessories	0.459	0.0235	0.789	0.518	0.128	0.088	0.076	0.066	0.049	0.022	0.027	0.012	0.012	Aug-00	Dec-99	Feb-96	Jul-11	41.2
Housing	0.177	0.0216	0.719	0.685	0.123	0.093	0.043	0.012	0.006	0.012	0	0.019	0.006	Dec-00	Jun-98	May-96	Jun-11	51.257
Furniture and HH Goods	0.456	0.014	0.795	0.466	0.146	0.104	0.078	0.049	0.039	0.039	0.029	0.019	0.032	Jul-01	Jul-00	Feb-96	Oct-11	46.903
Medical and Personal Care	0.399	0.0217	0.768	0.39	0.152	0.159	0.107	0.043	0.024	0.043	0.03	0.024	0.027	Oct-01	Dec-00	Feb-96	Aug-11	49.167
Transport	0.315	0.0221	0.766	0.438	0.172	0.094	0.056	0.043	0.107	0.026	0.03	0.026	0.009	Mar-03	Jun-01	Mar-96	Mar-12	52.967
Education and Entertainment	0.339	0.0337	0.669	0.279	0.164	0.145	0.134	0.095	0.063	0.035	0.052	0.015	0.019	May-01	Jul-00	Mar-96	Mar-12	45.508
Other G&S	0.412	0.0328	0.654	0.474	0.192	0.09	0.051	0.051	0.051	0.026	0.026	0.013	0.026	Aug-01	Nov-00	Apr-96	Jul-10	45.596
Core	0.398	0.2196	0.774	0.454	0.137	0.113	0.087	0.058	0.045	0.034	0.033	0.018	0.019	Apr-01	Jul-00	Feb-96	Mar-12	46.662
Non-Core	0.278	0.0495	0.638	0.504	0.155	0.117	0.07	0.018	0.076	0.015	0.023	0.021	0	May-02	Mar-01	Mar-96	Nov-11	51.729
All Goods	0.376	0.2691	0.75	0.46	0.14	0.114	0.085	0.053	0.049	0.032	0.032	0.019	0.017	Jun-01	Jul-00	Feb-96	Mar-12	47.48

Panel B: Core/Non-Core Groups

Group	$I(1)$	CPI Weight	$\widehat{E(\hat{\rho})}$	Number of Breaks in Trend $m=1$	$m=2$	$m=3$	$m=4$	$m=5$	$m=6$	$m=7$	$m=8$	$m=9$	$m=10$	$\widehat{E(\hat{T}_b)}$	$\widehat{Med(\hat{T}_b)}$	$\widehat{Min(\hat{T}_b)}$	$\widehat{Max(\hat{T}_b)}$	$\widehat{SD(\hat{T}_b)}$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Core: Goods																		
Food, Beverage and Tobacco	0.4	0.0594	0.81	0.488	0.114	0.11	0.077	0.048	0.048	0.043	0.034	0.023	0.016	May-01	Mar-00	Feb-96	Oct-11	48.341
Non-Food Merchandise	0.412	0.0512	0.793	0.455	0.14	0.105	0.086	0.061	0.044	0.039	0.03	0.019	0.021	Jan-01	Jul-00	Feb-96	Oct-11	45.163
Core: Services																		
Housing	0.31	0.0209	0.789	0.44	0.22	0.16	0.08	0.04	0	0	0	0.04	0.02	Jan-03	Oct-02	May-96	Jun-11	51.14
Education	0.212	0.019	0.537	0.213	0.176	0.176	0.148	0.102	0.066	0.033	0.053	0.012	0.02	Oct-01	May-01	Apr-96	Mar-12	46.191
Other Services	0.412	0.0649	0.695	0.521	0.127	0.108	0.073	0.048	0.037	0.02	0.033	0.013	0.02	Jun-01	Nov-00	Apr-96	Mar-12	47.225
Non-Core: Agricultural																		
Fruit and Vegetables	0.212	0.0061	0.574	0.654	0.078	0.131	0.052	0.026	0.02	0.007	0.026	0.007	0	Feb-01	Aug-99	Jul-96	Nov-10	40.833
Livestock	0.565	0.0338	0.83	0.5	0.12	0.08	0.12	0.02	0.08	0.02	0.04	0.02	0	Nov-01	Mar-01	Apr-96	Sep-11	49.123
Non-Core: Other																		
Energy	0.054	0.0039	0.856	1	0	0	0	0	0	0	0	0	0	Dec-03	Dec-03	Dec-03	Dec-03	0
Government Approved Fares	0.339	0.0094	0.688	0.343	0.25	0.114	0.071	0.014	0.136	0.021	0.014	0.036	0	Oct-03	Jan-03	Mar-96	Nov-11	57.947

Notes: For each group, Column (2) reports the fraction of goods and services that remain non-stationary after allowing for a fixed number of maximum structural breaks of $m = 10$ using the test in Kapetanios (2005) and Column (3) the total CPI weight for those goods that are non-stationary. Column (4) report the average estimated ρ in Equation (2) corresponding to the rejection of the null hypothesis. Columns 4-13 report the fraction of goods and services for which the estimated number of breaks is equal to $m = 1, \cdots, 10$ conditional on achieving stationarity. The last five columns report descriptive statistics for the estimated break date. For the case of more than one break these columns report the date corresponding to the rejection of the null hypothesis. All results were obtained by using a 95% significance level.

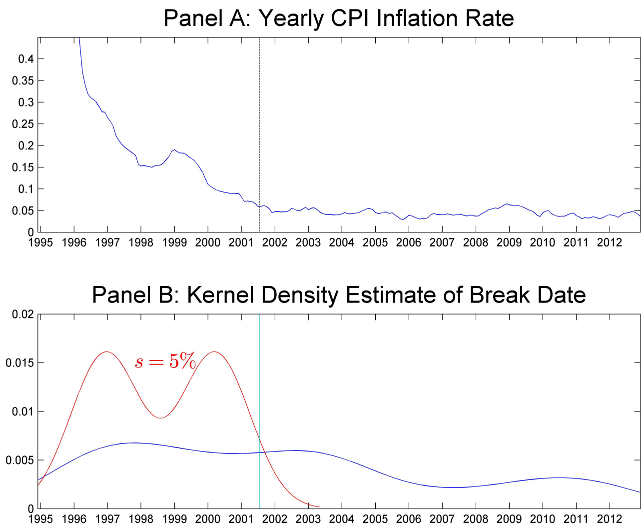

Figure 2: Panel A plots yearly CPI inflation rate along with the estimated break date (vertical, dotted line). Panel B plots a normal kernel density estimate for all good-city couples, conditional on experiencing at least one structural break with a 90 and 95% significance levels.

Table B3: Second Stage Results With 95% Significance Level

	LogNormal	Tobit	Linear Prob.
SAR (ρ_s)	-0.134***	1.497***	0.424***
	(0.02)	(0.01)	(0.04)
CPI Weight (γ_1)	-0.969	0.926	0.175
	(1.18)	(0.66)	(0.16)
CPI Weight^2 (γ_2)	1.284	-0.06	-0.036
	(2.29)	(0.15)	(0.03)

Notes: Table presents the estimated spatial and CPI weights marginal effects for the case of first-stage estimation of timing and likelihood of a break using 95% significance level.

Table B4: Determinants of Trend-Stationarity: City Fixed Effects

	LogNormal	Tobit	Linear Probability
Mexicali	-0.007	1.357***	0.049
	(0.06)	(0.22)	(0.04)
Juárez	-0.009	1.264***	-0.013
	(0.06)	(0.22)	(0.04)
Tijuana	-0.055	-0.173	0
	(0.06)	(0.22)	(0.04)
Matamoros	0.04	-0.383*	0.015
	(0.06)	(0.22)	(0.04)
La Paz	-0.073	0.338	0.005
	(0.05)	(0.22)	(0.04)
Acuña	-0.037	-0.88***	0.022
	(0.05)	(0.22)	(0.04)
Culiacán	-0.054	-0.29	0.04
	(0.06)	(0.22)	(0.04)
Hermosillo	-0.037	-0.775***	-0.005
	(0.06)	(0.22)	(0.04)
Huatapambo	-0.15**	-0.305	-0.046
	(0.06)	(0.22)	(0.04)
Tepic	-0.06	-0.37*	-0.051
	(0.05)	(0.22)	(0.04)
Monterrey	0.019	1.098***	-0.014
	(0.05)	(0.21)	(0.04)
Torreón	0.071	-0.674***	-0.019
	(0.06)	(0.22)	(0.04)
Tampico	0.037	0.128	0.022
	(0.06)	(0.22)	(0.04)
Chihuahua	-0.011	-0.397*	0.027

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Estimates for City Fixed Effects — Continued from previous page			
	LogNormal	Tobit	Linear Prob.
	(0.06)	(0.22)	(0.04)
Monclova	0.04	0.745***	-0.015
	(0.06)	(0.22)	(0.04)
Fresnillo	-0.107*	0.106	-0.018
	(0.06)	(0.22)	(0.04)
Jiménez	-0.035	-0.296	0.052
	(0.06)	(0.22)	(0.04)
Durango	-0.036	-2.157***	-0.022
	(0.06)	(0.22)	(0.04)
Morelia	0.072	-0.637***	0.001
	(0.06)	(0.22)	(0.04)
Guadalajara	-0.005	-0.499**	-0.022
	(0.06)	(0.22)	(0.04)
León	-0.037	1.157***	-0.04
	(0.05)	(0.22)	(0.04)
San Luis Potosí	0.03	-0.353	-0.036
	(0.06)	(0.22)	(0.04)
Aguascalientes	0.055	-0.721***	0.033
	(0.06)	(0.22)	(0.04)
Colima	-0.128**	1.898***	-0.001
	(0.06)	(0.22)	(0.04)
Jácona	-0.003	-0.313	0.039
	(0.06)	(0.22)	(0.04)
Cortázar	0.023	-0.343	0.032
	(0.06)	(0.22)	(0.04)
Querétaro	-0.057	-0.283	0.012
	(0.05)	(0.22)	(0.04)

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Estimates for City Fixed Effects — Continued from previous page

	LogNormal	Tobit	Linear Prob.
Tepatitlán	-0.032	0.034	0.007
	(0.06)	(0.22)	(0.04)
Acapulco	-0.003	-0.272	0.004
	(0.05)	(0.22)	(0.04)
Puebla	0.003	-0.083	0.011
	(0.06)	(0.22)	(0.04)
Toluca	0.056	-0.138	0.059
	(0.05)	(0.22)	(0.04)
Veracruz	0.023	0.232	-0.003
	(0.06)	(0.22)	(0.04)
Córdoba	0.032	0.03	0.008
	(0.06)	(0.22)	(0.04)
Iguala	0.027	-0.583***	-0.004
	(0.06)	(0.22)	(0.04)
Tulancingo	0.045	0.352	-0.029
	(0.06)	(0.22)	(0.04)
Cuernavaca	0.039	-0.301	0.002
	(0.06)	(0.22)	(0.04)
Tlaxcala	-0.007	0.113	-0.003
	(0.06)	(0.22)	(0.04)
San Andrés	-0.079	-0.182	-0.024
	(0.06)	(0.22)	(0.04)
Mérida	-0.031	0.42*	-0.013
	(0.06)	(0.22)	(0.04)
Tapachula	-0.009	-0.067	-0.027
	(0.06)	(0.22)	(0.04)
Villahermosa	-0.03	0.003	0.008

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Estimates for City Fixed Effects — Continued from previous page			
	LogNormal	Tobit	Linear Prob.
	(0.06)	(0.22)	(0.04)
Chetumal	-0.062	0.293	0.018
	(0.06)	(0.22)	(0.04)
Oaxaca	-0.094*	-0.495**	0.008
	(0.05)	(0.22)	(0.04)
Campeche	-0.009	-1.007***	0.055
	(0.05)	(0.22)	(0.04)
Tehuantepec	-0.153***	-0.075	0.026
	(0.06)	(0.22)	(0.04)

Notes: Table presents city fixed effects using as reference Mexico City. ***: statistically significant at 1% level, **: significant at 5% level, *: significant at 10% level. Standard errors in parenthesis with the following convention: See notes in Table (4).

Appendix C Robustness Checks

Table C1: Restricted Results for Robustness Checks

	Panel A: Robustness Check 1		
	Log Normal	Tobit	Lin.Prob
SAR (ρ_s)	-0.378***	0.719***	0.177***
	(0)	(0.02)	(0.05)
CPI Weight (γ_1)	0.304*	0.829	0.238*
	(0.18)	(0.82)	(0.14)
CPI Weight^2 (γ_2)	-0.047	0.935***	-0.086***
	(0.04)	(0.19)	(0.03)
	Panel B: Robustness Check 2		
	Log Normal	Tobit	Lin.Prob
SAR (ρ_s)	-0.419		
	(0.003)		
CPI Weight (γ_1)	0.338		
	(0.199)		
CPI Weight^2 (γ_2)	-0.052		
	(0.057)		
	Panel C: Robustness Check 3		
	Log Normal	Tobit	Lin.Prob
SAR (ρ_s)	-0.396***	0.377***	0.175***
	(0.00)	(0.01)	(0.04)
CPI Weight (γ_1)	1.102***	0.955	0.369
	(0.32)	(1.53)	(0.28)
CPI Weight^2 (γ_2)	-0.584	-0.185	-0.377
	(0.39)	(2.58)	(0.42)

Notes: In Panel A I exclude all the (g, c) couples with weights on the 30% upper tail of the distribution. In Panel B I estimate the Log Normal model with a Least Absolute Deviation median estimator. In Panel C I exclude Mexico City from the sample.