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Regional inflation persistence in Turkey

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Abstract

The purpose of the current study is to investigate the degree of inflation persistence, its geographical variation, sources of cross-regional variation, and presence of geographical/sectoral aggregation bias in national monetary policy. Our data set covers 26 NUTS-2 level Turkish regions and monthly CPI inflation over the period 2003–2019. We first estimate the degree of regional inflation persistence by autoregressive regressions, check its robustness against the presence of structural breaks (by Bai–Perron's algorithm) and nonlinearities (by Markovian Regime Switching regressions). Second, we examine the possibility of geographical and sectoral aggregation bias. Third, we investigate the cross-regional determinants of inflation persistence by panel data analysis, employing hybrid-effects spatial panel regressions. We analyze the direct and indirect effects of the determinants and test for regional spillover effects. Three main results are obtained. First, estimated persistence degrees are heterogeneous across regions. The geographical pattern is empirically robust against structural breaks and nonlinearities. We find that inflation persistence is distributed in a spatially correlated manner. Second, when sectoral and regional aggregation bias is tested, only sectoral aggregation indicates a considerable level of bias. Third, we find that the presence of large firms in the region and a higher share of agricultural output in GDP leads to lower persistence, while an increased share of industrial output, and increased trade volume leads to higher inflation persistence. Moreover, we find spatial spillovers of price variability evident in regression analysis. From a policy standpoint, it is required that structural policy programs are targeted to maintain flexibility in the regions where persistence is high (i.e., providing market entry/exit, institutional quality, policy credibility, stimulation of SMEs). Moreover, sectors that have high persistence, such as Hotels and Restaurants (persistence degree 0.55) and Health Services (0.39) should be weighted more in CPI calculations.

1 | INTRODUCTION

Inflation persistence is a phenomenon defined as the degree of rigidity in price adjustments toward a new equilibrium. It is characterized by sluggish responses of prices to real and monetary shocks (Ascari & Sbordone, 2014; Bernanke & Blinder, 1992; Christiano et al., 1999; Fuhrer & More, 1995). This has been recognized as a severe political problem, to such a degree that monetary policy is claimed to be ineffective under persistent inflation. In that case, controlling inflation is harder since prices do not move downwards easily even under strictly tight monetary regimes (Vaona & Ascari, 2012). Moreover, when persistence is high, the sacrifice ratio becomes higher as well which indicates greater loss in output during contractionary monetary policy periods (Brunello et al., 2001).

There is a large empirical literature targeted at investigating the degree and evolution of inflation persistence (Darvas & Varga, 2014). Altissimo et al. (2006) and Benigno and Lopes-Salido (2006) found heterogeneity in persistence across EU countries, whereas Gerlach and Tillman (2010) showed a decline in persistence following inflation targeting regime in Asian countries. Alvarez (2006) showed that prices are stickier in EMU countries compared to the United States (see Steinsson, 2003; Stock & Watson, 2007 for others).

The vast majority of these studies have, however, ignored the sub-national (regional) features. (Altissimo et al., 2006; Cecchetti & Debele, 2006; Dhyne et al., 2005). Some exceptions include Zsibók and Varga (2012), Tillman (2013), and Gajewski (2018).

Nonetheless, the regional aspect bears quite crucial policy implications. First, the regions which have persistent inflation suffer both in terms of difficulty in lowering inflation and having higher sacrifice ratios. Second, cross-regional heterogeneity in inflation persistence might cause severe Geographical Aggregation Bias. Central banks traditionally target the Consumer Price Index which represents the weighted average of regional inflation rates (Eusepi et al., 2009). However, there is a need for putting higher weight on the regions which have more persistence in prices. Failing to do so might, indeed, create a bias and policy distortions as the actual and optimal CPI values may deviate from each other (see Alp, 2010; Benigno, 2004 for sectoral aggregation bias).

With this study, our proposed contribution to the field is twofold. First, to the best of our knowledge, this paper represents the first attempt to analyze this issue for Turkish regions, even though there are various empirical studies performed at the country level (see, for instance, Çiçek & Akar, 2014; Keskek & Orhan, 2010)

Indeed, Turkey is a relevant place for study since inflation is historically one of the most severe macroeconomic problems in the country, which was particularly pronounced in 1980s and 1990s. (Dibooğlu & Kibritçioğlu, 2004). It has been driven mostly by currency depreciation shocks and large public deficits (Kibritçioğlu, 2002, 2004). While the inflation rate has been reduced remarkably after the adoption of implicit inflation targeting policy in 2002, it still represents a crucial concern. Furthermore, Turkey represents an interesting case since there are sizable spatial imbalances across regional economies, that is, in per capita incomes, industrial structures, and price movements, which makes our study more interesting per se (Duran, 2015; Duran & Erdem, 2017; Gezici & Hewings, 2007; Yıldırım & Öcal, 2006; Yıldırım et al., 2009).

Our second contribution is an improvement in understanding the reasons behind the cross-regional variation of inflation persistence. In the literature, the determinants have been analyzed with a quite limited focus on cross-regional dynamics. Among the few, one important variable is the degree of competition. There are two opposite views on it. On the one hand, it has been claimed that high competition leads to lower inflation persistence. The rationale behind this is the fact that firms under high competition are likely to change prices more frequently in a forward-looking behavior (Altissimo et al., 2006; Galí & Gertler, 1999; Leith & Malley, 2003). On the other hand, a counterview supports the idea that less competition (i.e., monopolistic or oligopolistic power) pushes firms to take control over the price and adjust it more frequently (Barro, 1972).

Another cross-regional determinant is the rigidity of the labor market. High unemployment, for instance, leads to inflation persistence as wages are not flexible in these systems and therefore cannot increase freely to cause demand-pull inflation (Brunello et al., 2001). Industrial mix is another explanatory variable that regions that include highly flexible sectors are likely to have less inflation persistence (Barsky et al., 2003; Erceg & Levin, 2006). Other less mentioned determinants are regional income level (Gajewski, 2018), inflation level (Sheshinsky & Weiss, 1977), and inflationary expectations (Cecchetti & Debelle, 2006). Our intention in this paper is to search for additional determinants, while testing in the meanwhile the validity of the above-explained variables.

Hence, the purpose of the current study is to investigate empirically the nature of regional inflation persistence, its degree, and geographical variation, cross-regional reasons, and the possibility of geographical/sectoral aggregation bias. Our data set covers 26 Nuts-2 level Turkish regions and monthly CPI inflation running from 2003:1 to 2019:4.

The organization of the rest of our study is as follows. Empirical analysis is carried out in Section 2 which is composed of three sub-parts. We first estimate (in 2.1) the degree of inflation persistence in regions by univariate autoregressive regressions and checked the robustness of our findings against the presence of structural breaks (by Bai–Perron's algorithm) and non-linearity (by Markovian Regime Switching regressions). Second (in 2.2), the possibility of Geographical and Sectoral Aggregation bias is examined. Third (in 2.3), cross-regional determinants of inflation persistence are investigated by spatial panel data regressions. Finally, the study is concluded in Section 3.[1]

2 | EMPIRICAL ANALYSIS

As an initial step to our analysis, it is useful to provide an overview of the NUTS (Nomenclature Units of Territorial Statistics) regions in Turkey. Turkish NUTS-2 level classification consists of 26 medium-scale regions, encompassing the 81 administrative regions (provinces) at the NUTS-3 level. NUTS-2 regions are referred to as socio-economic and statistical regions as the cities in these regions have mostly similar economic and industrial structures (Bernaciak, 2014; Beyhan, 2019; Lösch, 1938; Plapka et al., 2013). Their sectoral specialization is often homogenous, together with a similar level of development, income level, demographic, and labor market characteristics. Official regional statistics are provided mostly for these regions (see, Elburz et al., 2017; Elveren, 2010 who have used these regions in their analysis). They can also be seen as functional regions as there are strong commuting and trade/finance linkages among the cities within the regions (Beyhan, 2019; Karlsson & Olsson, 2006). We, therefore, prefer to pursue our analysis at the NUTS-2 regional level.

It is worthwhile to provide some background on the typical economic characteristics of the regions. We provide in Figure 1 a map demonstrating Turkish NUTS-2 regions. Istanbul (TR10), Izmir (TR31) and Hatay-Kahramanmaraş-Osmaniye (TR63) regions include big ports, hence harbor concentrations of industrial zones and establishments. Therefore, TR21, TR22, TR42, TR41, TR33, TR81, TR72, TR62, and TRC1 represent an industrial belt with intensive specialization in manufacturing and trade. Big metropolitan regions (such as Istanbul TR10, Ankara TR51 and Izmir TR31) are mostly placed in the Western part. They are developed regions with high income and high intensity of services sector (particularly, trade and finance). Regions close to Aegean and Mediterranean sea (TR32, TR61) are known as the tourism areas whereas Middle/Eastern/Northeastern regions (TR90, TR82, TR83, TR52, TR71, TRA1, TRA2, TRB1, TRB2, TRC2, TRC3) are the less developed regions in which agriculture and horticulture have relatively higher shares.

As a precursor to our analyses, we provide descriptive analysis and insights about the historical evolution of the inflation problem in Turkey. The regional, sectoral, and national inflation data used in this paper is obtained from the electronic sources of the Central Bank of the Republic of Turkey and Turkish Statistical Institute.

We depict in Figure 2 the national process of yearly CPI inflation from 1980 to 2018.

Since 1980, the liberalization and deregulation process in Turkey has accelerated the integration to foreign capital and output markets. During the 1980s and 1990s, most pegged exchange rate regime had been adopted. Short-term capital in and outflows had a deep impact on sharp currency devaluations which occurred in 1980, 1994, and 2001 (Bahmani-Oskooee & Domaç, 2003). These boom-boost cycles are recognized as one of the most important reasons for high inflation in Turkey. Moreover, political instability and large public budget deficits fell short of stabilizing aggregate demand that caused high inflation during this period (Metin-Özcan, 1998.

Looking at the values, CPI inflation was about 31% in 1980, it increased until 1994 hitting an enormous level, 110%, and tended to fall afterward. In 2002, implicit inflation targeting policy was adopted together with a flexible exchange rate regime, in 2006 explicit inflation targeting policy was started. After the crisis in 2001, inflation is stabilized reaching to lowest level of 6% in 2009 and 2011. In the most recent period, it has increased again due to the rapid depreciation of Turkish Lira and reached a level of 16% in 2018.

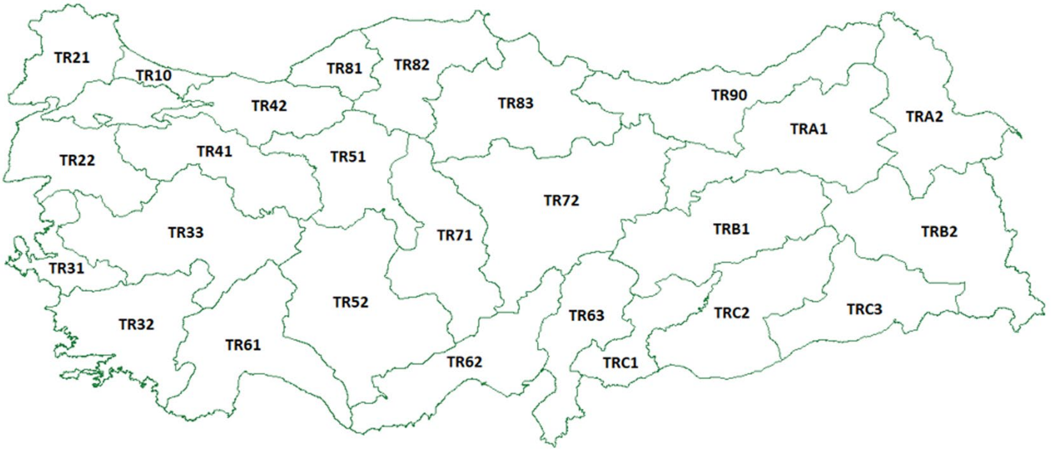

FIGURE 1 Map of Turkish NUTS-2 regions

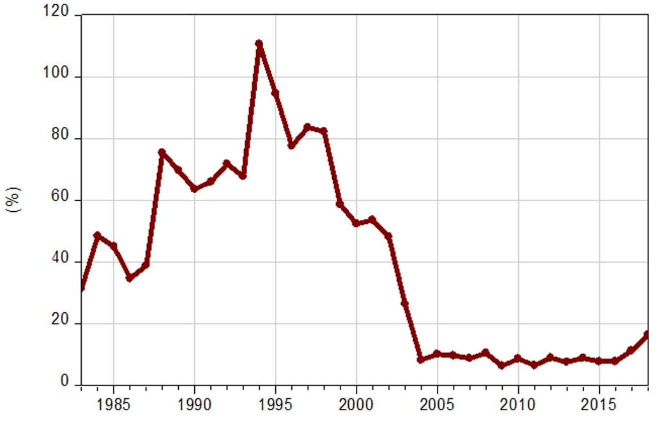

FIGURE 2 Evolution of yearly (1980–2018) inflation rates in Turkey. *Source*: Turkish Statistical Institute

Overall, Turkey has had a severe inflation problem over the last few decades, which necessitates more research focus on this topic. Also, the inflation problem is far less studied for regional economies in Turkey. Some exceptions studies were undertaken by Yeşilyurt and Elhorst (2014) and Yeşilyurt (2014), while the need for more research on this topic persists.

2.1 | Estimating regional inflation persistence

This section is devoted to the estimation of inflation persistence for regions. In the literature, three main methodologies have been used. First, univariate autoregressive functions in the following form have often been adopted (Altissimo et al., 2007; Barsky et al., 2003; Carlos, 2004; Clark, 2006; Erceg & Levin, 2006; Gajewski, 2018; Levin & Piger, 2004; Lünneman & Matha, 2004; O'Reilly & Whelan, 2005; Tillman, 2013; Vaona & Ascari, 2012)

$$\pi_t = \partial + \beta_1 \pi_{t-1} + \beta_2 \pi_{t-2} + \ldots + \beta_n \pi_{t-n} + \varepsilon_t \tag{1}$$

$$\rho = \sum_{i=1}^{n} \beta_i$$

where π_t represents monthly inflation rate whereas ρ denotes the degree of inflation persistence. Higher (lower) values of ρ indicate greater (lower) persistence. Gordon (1981) for instance estimated such an equation for United States over a period 1892–1979. He found that prices are getting more flexible over time. This method has been used by O'Reilly and Whelan (2005) and Levin and Piger (2004) as well. Likewise, Carlos (2004), Clark (2006), Erceg and Levin (2006), Altissimo et al. (2007), Barsky et al. (2003), and Lünnemann and Mathä (2004) applied a similar method in their country/sectoral level studies.

As a second method, measures such as frequency and volatility of price changes have been used (Taylor, 1981). Bils and Klenow (2004), Apel et al. (2005), Baharad and Eden (2004), and Baudry et al. (2004) attempted to measure for different countries the average duration of prices as a measure of rigidity and found that prices tend to change between every 4 months and 1 year (Chong et al., 2013). The third methodology uses the magnitude of the cumulative responses of prices to real and monetary shocks as a measure of flexibility (Chong et al., 2013).

The first method (univariate autoregression in Equation 1) is known to have well-known merits which are mostly related to accuracy, simplicity, and intuitiveness (Sims, 1980). To start with the accuracy, the autoregressive processes are known to be capable of estimating efficiently the degree of persistence in series. The persistence is determined by the strength of the relation between current and past values. Since this measure represents the degree of path dependence, it can be used as an indicator of price stickiness/rigidity. Moreover, it is simple to apply this technique which has been used quite often in the literature. Furthermore, the outcome is intuitive and easily understood as high values of ρ represents stronger association between current and former values of inflation, indicating a high level of persistence. Indeed, Andrew and Chen (1994) recognized "ρ" as the best measure of persistence, referring to the monotonicity of the relationship between "ρ" and cumulative IRF (Impulse-Response Function). For these reasons, this technique is quite commonly used to measure inflation persistence (Altissimo et al., 2007; Barsky et al., 2003; Carlos, 2004; Clark, 2006; Erceg & Levin, 2006; Levin & Piger, 2004; Lünnemann & Mathä, 2004; O'Reilly & Whelan, 2005). Thus, we adopt the methodology in our study.

In contrast, the drawback of the method is the possible bias in estimations that might be driven by structural breaks and functional misspecification problems (Levin & Piger, 2004) which we intend to control for the sake of robustness.

There exist some other structural models that incorporate normal rigidities such as the Phillips curve and price adjustment mechanisms (i.e., Calvo, 1983). However, the first method (autoregressive approach) is found to outperform these models statistically (Franta et al., 2010).

Before proceeding to the main analysis, time series properties of the variables are checked. First, the monthly evolution of national CPI inflation (in natural logs and first differenced CPI) is illustrated in Figure 3. At a glance, a quite clear stationary evolution is observed. To provide a formal examination, an Augmented Dickey-Fuller (ADF) test is applied to regional inflation series (Dickey & Fuller, 1979). As an outcome, it is seen in Table 1 that all series are stationary at levels as McKinnon test statistic is always above the critical value. Hence, we can safely proceed to our analysis with the variables in levels.

We apply the autoregressive model in Equations (1) to 26 Regions and the aggregate economy (Sims, 1980). The seasonality in the series is treated by adopting a Multiplicative Ratio to Moving Average method. Lag length is determined on the basis of Akaike Information Criterion (AIC) where the maximum lag length is set to 24 months (Akaike, 1973). The outcome of the estimation is presented

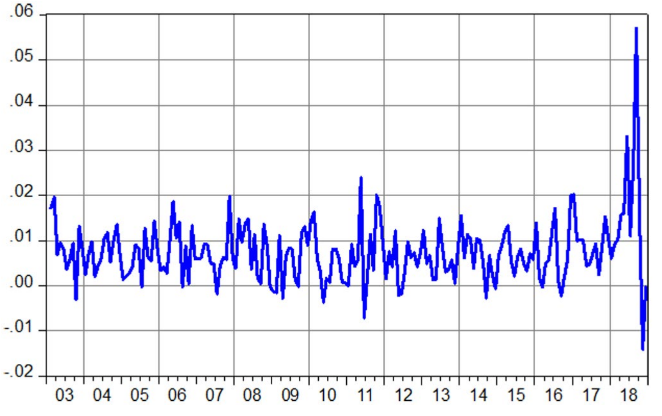

FIGURE 3 Evolution of monthly (2003–2019) Inflation Rates in Turkey. *Source*: Turkish Statistical Institute

TABLE 1 Unit root analysis, ADF test results

Region	ADF McKinnon statistic	Region	ADF McKinnon statistic
Turkey	−6.800***		
TR10	−6.801***	TR71	−10.799***
TR21	−5.490***	TR72	−6.774***
TR22	−7.574***	TR81	−10.977***
TR31	−11.886***	TR82	−10.985***
TR32	−4.736***	TR83	−10.026***
TR33	−9.686***	TR90	−9.246***
TR41	−10.513***	TRA1	−9.267***
TR42	−11.425***	TRA2	−6.905***
TR51	−9,426***	TRB1	−6.805***
TR52	−6.890***	TRB2	−10.723***
TR61	−6.698***	TRC1	−10.147***
TR62	−7.215***	TRC2	−11.473***
TR63	−6.693***	TRC3	−9.476***
Critical values			
1%	5%	10%	
−3.465	−2.877	−2.575	

Note: Lag length was determined on the basis of AIC where maximum lag is set as 24 months.

***Statistical significance at 1%;

**statistical significance at 5%;

*statistical significance at 10%.

in Table 2. Histogram normality diagnostic tests are applied and the outcomes are unproblematic in all cases (Jarque & Bera, 1980). Errors are found as normally distributed.

The calculated persistence degree is presented in a raw just below the parameter estimations (highlighted with a gray color). At a glance, persistence degree is found to be 0.18 at the national level. However, it does vary considerably across regions. The region that has the highest persistence is TR32 ($\rho = 0.36$) and the region with highest price flexibility is TR22 ($\rho = 0.003$).

It is useful to provide an overview of the reasons for extreme persistence/flexibility degrees and related characteristics of these regions. TR32 region (Muğla-Denizli-Aydın Provinces) is placed on the Southern/Aegean Sea coast (as seen in Figure 1.) It is firmly a tourism region (Particularly Muğla and Aydın provinces), including some light manufacturing and agriculture as well in the inner parts. We have checked the inflation persistence of the tourism sector (transportation, hotels, and restaurants) and found that it has relatively higher persistence. Such that, *hotels and restaurants* sector has the persistence degree 0.55 and transportation sector has the persistence degree 0.3 which are above the general average. So, it may be argued that high inflation persistence might be driven by the Tourism sector's rigid price characteristics.

The TR22 region (Çanakkale-Balıkesir Provinces) is the region with lowest inflation persistence, which is located on the north-western coast. Agriculture and horticulture have an important share in this region's economy as well as some less industry/manufacturing. Particularly agriculture and horticulture sectors are known to having less inflation persistence. Hence, it might be argued that low inflation persistence might be driven by Agriculture's relatively flexible price characteristics.

TABLE 2 Univariate AR regressions and estimation of inflation persistence

				TR22	TR31	TR32	TR33	TR41	TR42	TR51	TR52	TR61	TR62	TR63
π(−1)	0.339901	0.320608	0.233748	0.226302	0.145247	0.364164	0.36	0.264118	0.187911	0.291462	0.212918	0.327112	0.215139	0.343583
SE	−0.07363	−0.07316	−0.07361	−0.07301	−0.07191	−0.07404	−0.0719	−0.07	−0.07108	−0.07231	−0.07314	−0.07379	−0.07344	−0.07419
t-Statistics	[4.61642]	[4.38205]	[3.17563]	[3.09946]	[2.01984]	[4.91857]	[5.01797]	[3.77331]	[2.64356]	[4.03054]	[2.91105]	[4.43314]	[2.92950]	[4.63120]
π(−2)	−0.167347	−0.10802	−0.12994	−0.15115		−0.25498	−0.19791			−0.13667	−0.14463	−0.13402	−0.07522	−0.20364
SE	−0.0778	−0.07756	−0.07544	−0.07448		−0.07951	−0.07324			−0.0742	−0.07586	−0.07723	−0.07535	−0.07867
t-Statistics	[−2.15106]	[−1.39272]	[−1.72256]	[−2.02943]		[−3.20673]	[−2.70201]			[−1.84184]	[−1.90649]	[−1.73530]	[−0.99832]	[−2.58840]
π(−3)	0.173808	0.171334	0.118254	0.142513		0.195401					0.127737	0.154855	0.123668	0.114066
SE	−0.0783	−0.07738	−0.07523	−0.07438		−0.07935					−0.07491	−0.07798	−0.07439	−0.07875
t-Statistics	[2.21982]	[2.21422]	[1.57188]	[1.91607]		[2.46240]					[1.70531]	[1.98592]	[1.66233]	[1.44841]
π(−4)	−0.165552	−0.18194	−0.15948	−0.21449		−0.09057						−0.16401	−0.16542	−0.09205
SE	−0.08798	−0.08411	−0.084	−0.08246		−0.09047						−0.0914	−0.0.844	−0.08692
t-Statistics	[−1.88160]	[−2.16328]	[−1.89852]	[−2.60120]		[−1.00118]						[−1.79436]	[−1.95993]	[−1.05900]
π(−5)						0.145807								
SE						−0.08778								
t-Statistics						[1.66113]								
Constant	0.005998	0.005887	0.006904	0.007594	0.006506	0.004837	0.0062	0.005431	0.006106	0.006295	0.005983	0.005903	0.006787	0.006219
SE	−0.00102	−0.001	−0.00111	−0.00116	−0.00078	−0.00115	−0.00083	−0.00073	−0.00081	−0.00085	−0.00107	−0.00102	−0.00111	−0.00111
t-Statistics	[5.86497]	[5.87169]	[6.20437]	[6.56818]	[8.37948]	[4.21913]	[7.47740]	[7.47770]	[7.58064]	[7.44643]	[5.61028]	[5.78165]	[6.11697]	[5.62664]
Persistence degree (ρ)	0.18081	0.20198	0.062576	0.003182	0.145247	0.359824	0.162882	0.264118	0.187911	0.154797	0.196028	0.183941	0.098164	0.161961
Jarque Bera														
Normality Test Statistic	546.4509	204.7867	513.5075	348.3536	474.4375	344.7096	1316.607	489.3206	814.3596	386.5156	984.0886	1321.072	736.211	465.796
Detected Break Dates	2016-M9	2016-M9	2016-M9	2016-M9	2016-M9	2016-M9	2016-M9	2016-M9	NONE	2016-M9	2016-M9	2016-M9	2016-M9	2016-M9

(Continues)

TABLE 2 (Continued)

				TR22	TR31	TR32	TR33	TR41	TR42	TR51	TR52	TR61	TR62	TR63
Variables	TR71	TR72	TR81	TR82	TR83	TR90	TRA1	TRA2	TRB1	TRB2	TRC1	TRC2	TRC3	
$\pi(-1)$	0.232289	0.290108	0.219585	0.214705	0.211644	0.294751	0.348257	0.302412	0.266989	0.240615	0.251969	0.176367	0.239561	
SE	−0.07109	−0.074	−0.0711	−0.07149	−0.07194	−0.0728	−0.07244	−0.07334	−0.07312	−0.07082	−0.07194	−0.07179	−0.07201	
t-Statistics	[3.26741]	[3.92063]	[3.08847]	[3.00327]	[2.94214]	[4.04901]	[4.80720]	[4.12338]	[3.65126]	[3.39776]	[3.50272]	[2.45670]	[3.32689]	
$\pi(-2)$		−0.14771			−0.14304	−0.12268	−0.15266	−0.15189	−0.14252		−0.18206		−0.09739	
SE		−0.07694			−0.07293	−0.07407	−0.07356	−0.07707	−0.07714		−0.07382		−0.07254	
t-Statistics		[−1.91970]			[−1.96136]	[−1.65637]	[−2.07532]	[−1.97094]	[−1.84762]		[−2.46623]		[−1.34252]	
$\pi(-3)$		0.141634						0.101995	0.118813					
SE		−0.07753						−0.07501	−0.07503					
t-Statistics		[1.82694]						[1.35982]	[1.58349]					
$\pi(-4)$		−0.1377												
SE		−0.08604												
t-Statistics		[−1.60041]												
$\pi(-5)$														
SE														
t-Statistics														
Constant														
SE	0.005763	0.00644	0.005763	0.005784	0.006946	0.006188	0.005978	0.005765	0.005523	0.005783	0.007124	0.006377	0.006011	
t-Statistics	−0.00079	−0.00113	−0.0008	−0.0008	−0.00095	−0.00089	−0.00085	−0.00102	−0.001	−0.00078	−0.00097	−0.00085	−0.00092	
	[7.31709]	[5.72125]	[7.22437]	[7.24232]	[7.27757]	[6.92343]	[7.07096]	[5.67694]	[5.51432]	[7.37708]	[7.36543]	[7.52308]	[6.54283]	
Persistence degree (ρ)	0.232289	0.146335	0.219585	0.214705	0.068605	0.172067	0.195593	0.252514	0.243278	0.240615	0.069912	0.176367	0.142174	
Jarque Bera Normality Test Statistic	288.1987	270.4846	777.0449	415.8386	919	847.9269	564.5358	1097.29	274.4881	1697.16	1333.263	211.3722	338.2942	
Detected Break Dates	2016-M9	2016-M5	NONE	2016-M5	2016-M6	2016-M6	2016-M9	2016-M9	2016-M9	NONE	2016-M9	2016-M5	2016-M3	

Note: Bai–Perron (2003a, 2003b)'s algorithm is used to detect structural breaks, maximum breaks allowed:5, significance = .05.

Our findings indicate that cross-regional average of persistence degree is 0.175 whereas the standard deviation is 0.07. It is useful to compare these results with the ones in the literature. For instance, Vaona and Ascari (2012) have estimated the same parameter by employing a quarterly data set over a period 1996–2006 for 103 Italian provinces and found that the average degree of persistence is 0.25 (where standard deviation is 0.24). Tillman (2013), who estimated yearly inflation persistence for Korean metropolitan cities and provinces for a period 1990Q2–2011Q1, found that persistence degree ranges between 0.13 and 1.15 in the pre-1997 period, while it ranges between 0.13 and 0.65 in the pre-1998 period and between 0.15 and 0.44 in the post-1999 period. Hence, prices are shown to become more flexible over time. Gajewski (2018) analyzed 16 Polish Nuts-2 regions over the period 2005Q1 to 2016Q3 and found that quarterly inflation persistence varied between 0.52 and 0.73. Overall, the Turkish case is roughly similar to what is observed in Italy, Korea, and Poland.

The geographical distribution of the persistence degree is illustrated in Figure 4. The dark-gray color represents the regions that have highest persistence whereas the light-gray color represents the places that have more flexible prices.

Some interesting features appear to emerge from the map. First, the corridor between Istanbul and Ankara, which represents an industrial belt, has relatively higher inflation persistence. Second, Eastern/Northeastern Anatolian regions that have agriculture/horticulture based economic systems have relatively higher persistence. Third, the Aegean/Mediterranean regions of the west coast from Aydın to Antalya, which represent a tourism belt, have relatively more persistent prices. In contrast, some northwestern regions (TR21, TR22,) which represent the agriculture and industrial zone, as well as some southern (TR62, TRC1) and Black Sea regions (TR83), have the least persistence.

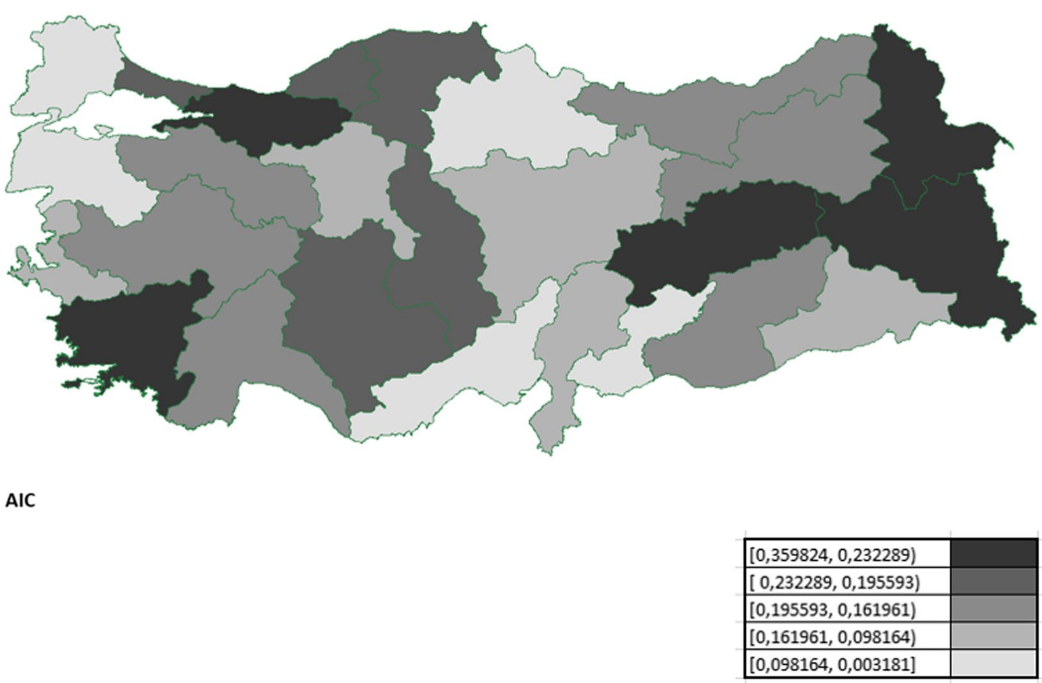

FIGURE 4 Geographical distribution of inflation persistence. Lag length was determined on the basis of AIC where maximum lag is set as 24 months

2.1.1 | Robustness analysis

Three types of robustness controls are applied to check the validity of the regional distribution of persistence. To first one is related to lag length used in autoregressive functions. Rather than using AIC, we now fix the lag length as 4 months, and re-estimate Equation (1) for all regions. We do these analyses since different lag lengths applied to regions might significantly affect the estimated degree of persistence.

As an outcome, the calculated persistence degrees are presented in Figure 5. The values are quite similar to the original findings in Figure 4. The geographical pattern seems very similar to the original map. The correlation coefficient between the two maps (Figures 4 and 5) is higher than 0.75. Hence, one may argue that our results are robust with respect to lag length choice.

The second robustness check is related to a concern that the presence of potential structural breaks in the autoregressive equations may lead to biased estimates (Pesaran & Timmermann, 2005; Stock & Watson, 1996). This concern has been reiterated and empirically controlled by various scholars. For instance, Vaona and Ascari (2012) and Levin and Piger (2004) applied Wald structural break and robustness tests. Perron (1989) claims that failing to incorporate these breaks causes the overestimation of the persistence parameter.

Hence, we apply Bai and Perron's (1998) famous algorithm that enables detecting unknown multiple break dates in regression models (see Bai & Perron, 1998, 2003a, 2003b; for technical details). The detected break dates are presented in the final row in Table 2.

In terms of results, a break is detected in 23 of the 26 regions. The breaks are identified generally between months 2016M3 and 2016M9. Following these breaks, persistence has been observed to decrease considerably together with rising rates of inflation and its volatility.

Potential reasons behind the break in 2016 are numerous. After this year, inflation volatility, expectations, and uncertainty all increased. In theory, high level of inflation and related expectations are claimed to increase the frequency of price changes (Sheshinsky & Weiss, 1977). Moreover, forward-looking inflationary expectations, possibly, lead to more flexible prices (Cecchetti & Debelle, 2006; Gajewski, 2018).

After the 2008/2009 Global financial crisis, economic growth rates in Turkey were high. Foreign direct investment and portfolio investment inflows were quite adequate. By 2015, however, a high current account deficit was observed due to massive imports of raw materials and intermediate goods. This has increased concerns on the exchange rate, inflationary expectations, and uncertainty.

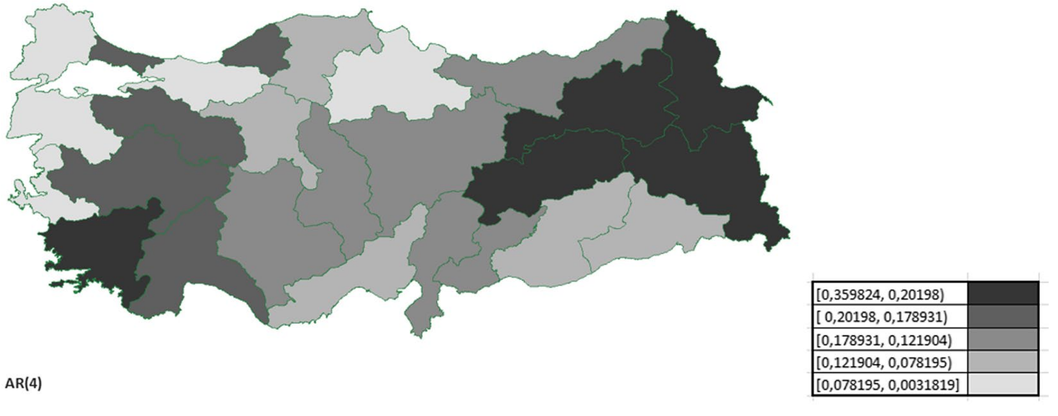

FIGURE 5 Geographical distribution of inflation persistence. Lag length is 4 months

By 2018, unsustainability of high current account deficit has created pressure on the exchange rate. Consequently, Turkish Lira has depreciated considerably against US Dollar in 2018, also due to some international political problems. Most recently, in 2019, it has appreciated again to some extent and current account deficit has declined slightly.

These developments are illustrated by key indicators in Figure 6 below. First, as seen in Figure 6a, foreign debt stock/GDP has increased from about 30% in 2010 to about 60% in 2015 and to about 70% in 2018 and fall back to about 60%–65% in 2019, that exhibits the extent of the problem related to high current account deficit and its unsustainability.

From a supply side viewpoint of inflation, volatility in the exchange rate and producer prices have increased remarkably after 2016 as illustrated in Figure 6b,c. Although these volatilities have decreased to some extent by 2019, possibly, these developments have contributed to cost-push inflation. From a demand-side view, total consumption expenditures have become more volatile as well, which had led to more volatile inflation especially between 2016 and 2017 (as observed in Figure 6d). Hence, all these factors have increased the inflation and frequency of price changes after 2016, that is why we observed a structural break in inflation persistence.

We include the break dates as time dummies in Equation (1) for each region and re-estimate the persistence parameters by AIC and AR(4) lag lengths. As an outcome, the estimated persistence parameters are displayed in Figure 7. The values are much lower once structural breaks are involved. This is in line with the claim of Perron (1989) that the original values in Figure 4 are upward biased.

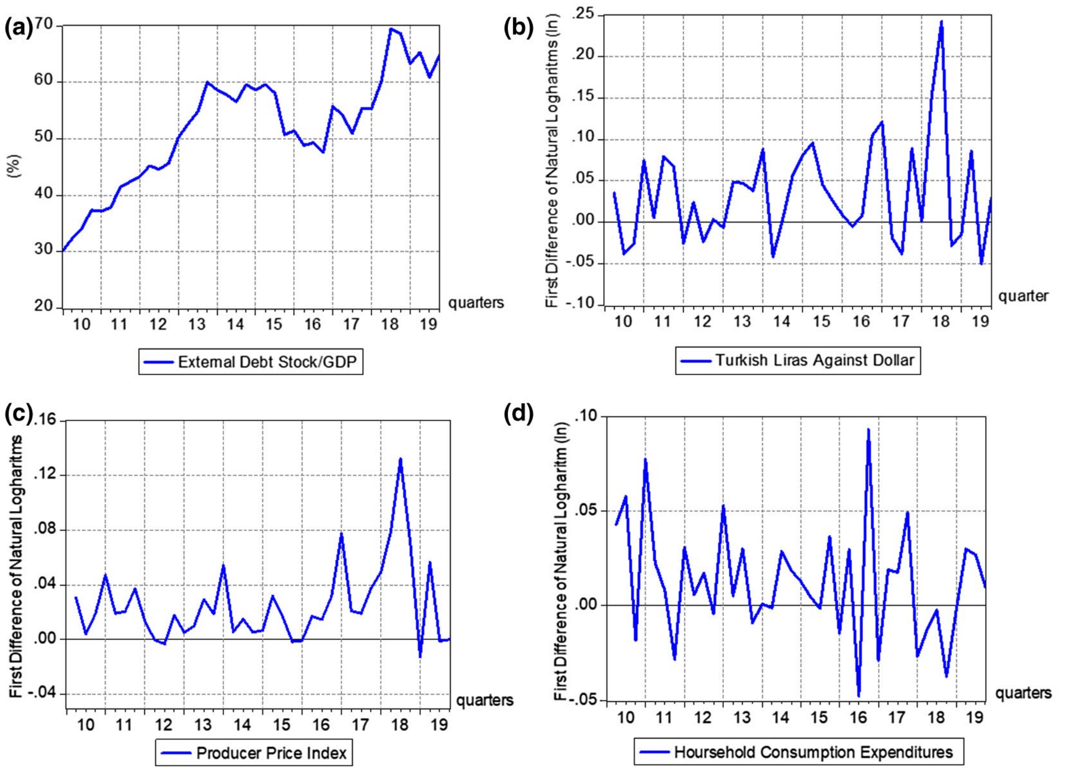

FIGURE 6 Recent evolution of Macroeconomic and stability related variables in Turkey. *Source*: for 6.a. Central Bank of the Republic of Turkey, Turkish Statistical Institute. For 6.b tr.investing.com, for 6.c. and 6.d. Turkish Statistical Institute

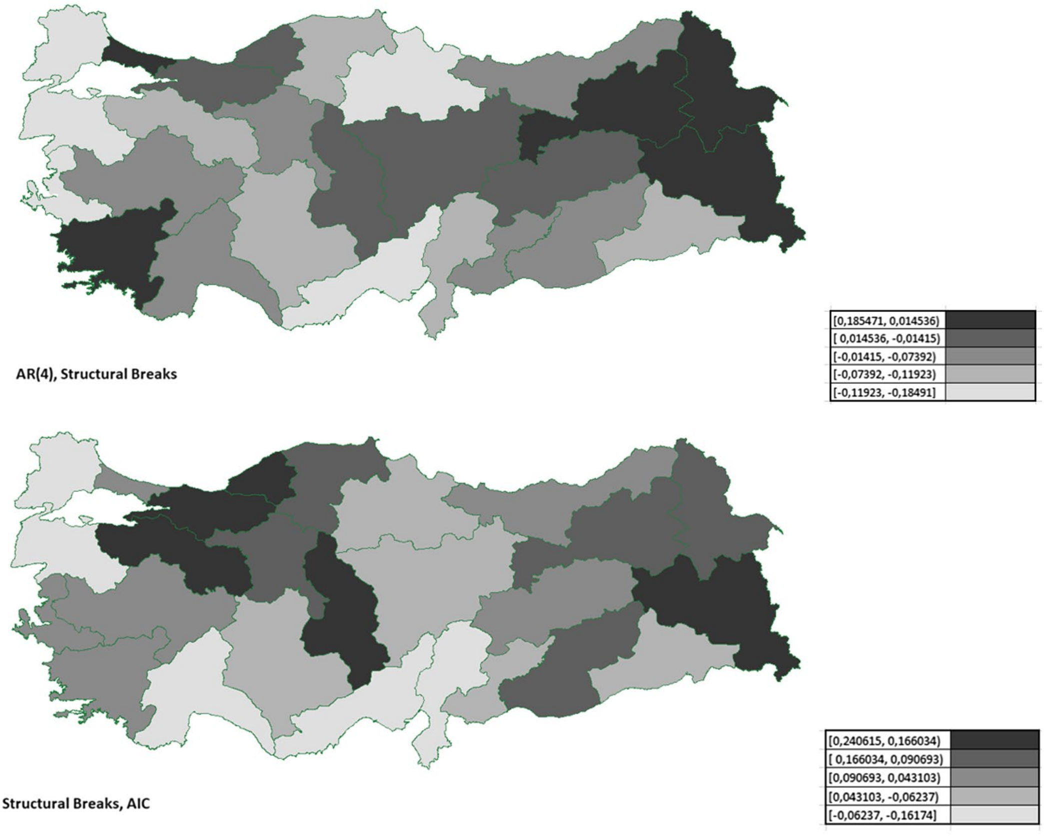

FIGURE 7 Geographical Distribution of Inflation Persistence, structural breaks controlled

One important result, more interestingly, shows that the relative position of regions does not change much. The geographical picture looks more or less the same as in the original map (Figure 4).

Hence, one may argue that our results regarding the regional distribution of persistence are robust with respect to the presence of structural breaks, although the levels of persistence are not.

A final robustness check is related to possible non-linearity in the autoregressive equations, the presence of which might seriously bias the estimated degree and geographical distribution of inflation persistence. To do so, we refer to Hamilton's (1989) Markov Regime Switching model that enables testing whether or not there is only one regime parameter estimate or two different regimes of estimated parameters. The former case indicates the validity of linearity but the latter implies the violation of linearity. (see Hamilton, 1989; Owyang et al., 2005 for technical details).[2] We apply the model for 26 regional monthly inflations by the AIC criterion.

The regime probability for national data is depicted in Figure 8. The first regime is the low persistence regime during which persistent degree is low and whereas the second regime represents the high persistence regime.

As seen clearly, the probability of low persistence regime is dominant and has almost always higher values than the second one. In only 7 months, regime 1's probability is higher than 0.5 whereas in the remaining 189 months' regime 0's probability is higher.

Hence, one may argue that there is one robust low persistence-regime and the second regime is statistically weak. Therefore, we may consequently argue that linearity assumption is plausible as the nonlinearity in Markov switching regression is weakly evident.

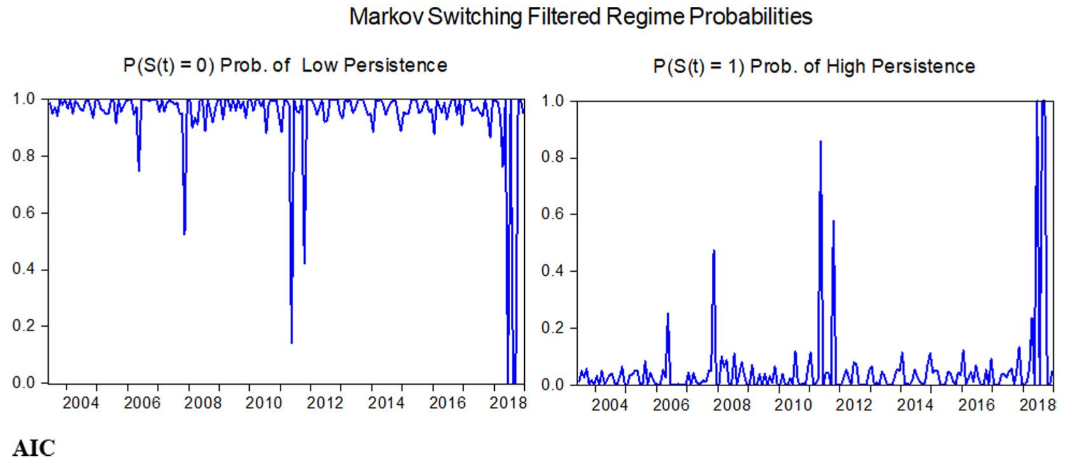

FIGURE 8 Regime probabilities for parameters, national monthly CPI inflation

TABLE 3 Moran's I spatial dependence test results

Test type	Moran's I statistic	*p* value
Persistence degree (AR4)	0.2307**	0.0166
Persistence degree (AIC)	0.0209	0.3147
Persistence degree (AR4-with structural breaks)	0.1448*	0.0730
Persistence degree (AIC-with structural breaks)	0.2644***	0.0097

***Statistical significance at 1%;

**Statistical significance at 5%;

*Statistical significance at 10%.

Overall, the lesson we get from this analysis is that the geographical distribution of estimated autoregressive parameters is robust with respect to the existence of structural breaks, possible nonlinearities and different lengths of time lags as the maps in Figures 4, 5, and 7 well coincide with each other.

One important subject that of our interest is the spatial distribution of inflation persistence. We intend to investigate the extent to which it follows a distinct spatial pattern. Looking at the geographical distribution in maps (Figures 4, 5, and 7), it is visually inspected to be spatially correlated, at least for an important fraction of regions. Particularly, Eastern Anatolian regions have high persistence degrees and it seems a spatial clustering there. Likewise, regions around the Istanbul port (TR10), the regions around western Mediterranean coastal cities (TR32) tend to exhibit high degrees. Some other parts in the north-western regions (TR 22, TR21) and eastern Mediterranean regions (TR62, TR63) show low inflation persistence.

To complement formally the result of spatiality, we performed a Moran's I test statistics to the inflation persistence degrees obtained by estimating equation 1 using (i) lag length of 4 months, (ii) lag length determined by AIC, (iii) lag length of 4 months and structural breaks controlled and (iv) lag length determined by AIC and structural breaks are controlled. In terms of Spatial Weight Matrix, the 26×26 spatial contiguity matrix, by queen contiguity with 10 km. precision and in row-standardized form is used (Anselin, 1988; Moran, 1950).

The results are presented in Table 3. As an outcome, the positive spatial correlation is found evident. It is found statistically significant in 3 (out of 4) specifications. Therefore, one may argue that inflation persistence follows a positive spatial dependence that high and low inflation persisted regions tend to concentrate geographically.

Overall, the observed geographical pattern, spatiality, and the underlying reasons are complex and, therefore, not explained easily. Thus, there is a need for a formal analysis which will be pursued in Section 2.3.

2.2 | Is there a geographical aggregation bias?

As anticipated in the introduction, central banks traditionally target lowering the aggregate CPI inflation which can be seen as the weighted average of sectoral rates. However, there are claims that policy makers should put more weight on sectors that have more persistence in price movements (Alp, 2010; Benigno, 2004; Cecchetti & Debelle, 2006). Otherwise, monetary policy deviates from optimality and distortions may occur. Indeed, there are findings in the literature that show quite varying persistence degrees across sectors. Altissimo et al. (2007) have found that inflation is more persistent in food, housing, and transportation and less persistent in health services, furniture, alcohol, and tobacco. Erceg and Levin (2006), Babecký et al. (2009) found that nondurables and raw material sectors have less persistent inflation rates.

Interestingly, a similar bias can theoretically be driven by also geographical aggregation (Eusepi et al., 2009; Pino et al., 2016). In that case, weighted averages of the regional CPI inflations may lead to a policy distortion. Central banks should, therefore, assign more weight to the regions which have higher inflation persistence. Otherwise, targeted CPI can be different than the optimal one. The importance of this fact has been emphasized by Vaona and Ascari (2012) but they found no geographical aggregation bias in the Italian case.

To test the sectoral and geographical aggregation bias, we refer to the measure (Benigno, 2004; Eusepi et al., 2009; Pino et al., 2016 Vaona & Ascari, 2012).

$$WS_i = \frac{\rho_i W_i}{\sum_{i=1}^{n} \rho_i W_i} \tag{2}$$

where WS represents the weights calculated with respect to the weight of the sector in CPI market basket (*Wi*) and inflation persistence degree of the sectors, notated by ρ. Namely, these sectors are the followings with following weights in the official CPI market basket; Food and Beverage (23.3%), Clothing (7.2%), Alcoholic Drinks and Tobacco (4.2%), Health Services (2.6%), Education services (2%), Communication (3.7%), Entertainment (3.3%), Housing (15.1%), Transportation (16.8%), Furniture (8.3%), Otel and Restaurant (8%) and other goods and services (5%).

Moreover, once we estimate the sectoral degrees inflation persistence, sectors that have highest values are Hotels and Restaurants (persistence degree: 0.55), Health Services (0.39), Furniture (0.33), Transportation (0.3), Housing (0.28), other goods and services (0.27), Entertainment (0.26), Communication (0.11), Education services (0.03), Alcoholic Drinks and Tobacco (0.0006) , Clothing (−0.30 but assumed as 0) and Food and Beverage (−0.33 but assumed as 0).

Similarly, WR represents the weights calculated with respect to regional GDP size (W_j) and inflation persistence degree of the regions, denoted by ρ_j. (Benigno, 2004; Eusepi et al., 2009; Vaona & Ascari, 2012).

$$WR_j = \frac{\rho_j W_j}{\sum_{j=1}^{k} \rho_j W_j} \tag{3}$$

The evolution of official inflation and the inflation series that are calculated by weighting with respect to *WS* and *WR* are depicted in Figure 9.

It is clearly seen that that there is no serious geographical aggregation bias. In 7.a, we illustrate the evolution of official CPI inflation and the inflation rates obtained by weighting with respect to regional persistence degrees (WR). We report estimates based on AR(4) specifications as well as the AIC criterion for lag length determination. The evolutions of all series seem to move almost with perfect synchronization. The Pearson correlations between official CPI inflation and the other two are both 0.99.

With regard to sectoral aggregation bias, it has been observed in 7.b that there is a moderate level bias. It is illustrated the evolution of official CPI inflation and the inflation series obtained by weighting sectors with respect to *WS*. The evolutions of calculated series do not seem to move always synchronously with official inflation, and the Pearson correlation between official CPI inflation and the other two is about 0.77. Thus, the Central Bank should consider this fact and assign higher weight to the sectors with higher inflation persistence. Hence, we may argue that there exists no geographical aggregation bias but there is a moderate level of sectoral aggregation bias.

2.3 | Cross-regional determinants of inflation persistence

In this section, we investigate the factors that contribute to inflation persistence using panel data analysis. The issue why some regions have more persistent inflation have received scant attention in the empirical literature. There are, however, few hypotheses.

First, the level of competition in the regional economy is put forward. There are two opposite views on it. One hypothesis supports the idea that high competition in regional markets leads to less persistence. It is claimed that when firms face hard competition, they are more likely to adjust the prices in a forward-looking manner (Leith & Malley, 2003; Vaona & Ascari, 2012). In a similar vein, a stream of supporters, adopting a New Keynesian perspective, states that it is required rule of thumpers among price setters and firms under high competition will change prices more rapidly (Altissimo et al., 2006; Galí & Gertler, 1999; Vaona & Ascari, 2012). An opposite hypothesis claims that firms

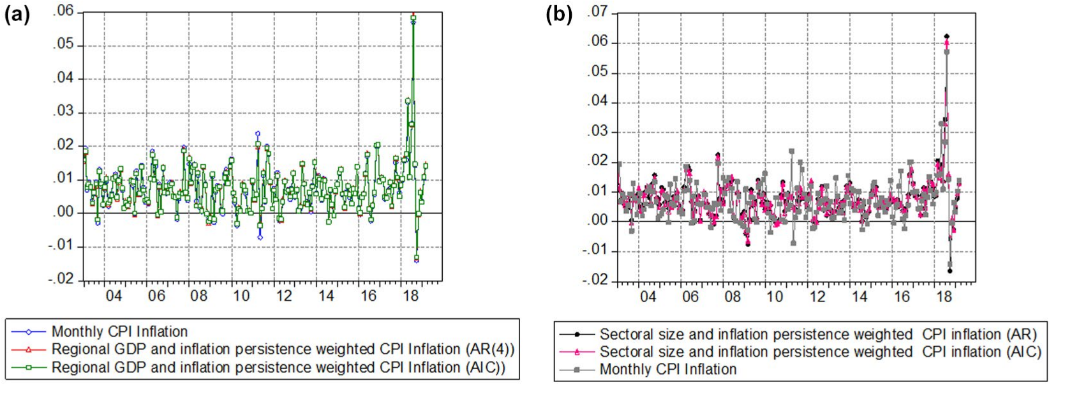

FIGURE 9 Regional and sectoral aggregation bias

under milder competition (i.e., monopolistic or oligopolistic environment) are likely to have control over the price and change it more frequently (Chong et al., 2013).

As a second hypothesis, inflation persistence is positively associated with high unemployment and wage rigidity (Brunello et al., 2001). Under strict labor market legislation, wages are expected to be more rigid, thus, unemployment is expected to be higher. As wages are not flexible enough, they can hardly adjust toward a new equilibrium in case of shocks. This hampers the flexible movement of prices and creates the persistence of inflation in the regions in which unemployment is higher.

Third, the industrial structure is regarded as an important variable. Regions that specialize in more competitive and flexible sectors are likely to experience less persistence (Vaona & Ascari, 2012). However, there are quite mixed results in the existing studies. For instance, while Chong et al. (2013) has found that agriculture has quite volatile prices, Babecký et al. (2009) have found that raw materials/nondurable industrial goods have less persistence.

Fourth, level of income is found as an explanatory variable that more prosperous regions are observed to have less inflation persistence in Polish (Gajewski, 2018) and Italian cases (Vaona & Ascari, 2012).

Fifth, it is claimed that the level of inflation and type of inflationary expectations are influential on persistence. High level of inflation is likely to increase the frequency of price changes (Sheshinsky & Weiss, 1977). In contrast, low levels of inflation lead to persistence as the cost of keeping prices constant is less and, in such case, firms prefer longer contracts (Assarsson, 1986). With regard to the impact of expectations, if backward, the more the persistence is observed. Controversially, in case of forward-looking expectations, prices are expected to be fully flexible (Cecchetti & Debelle, 2006; Gajewski, 2018).

In order to examine the above-mentioned hypotheses as well as additional ones, we construct a panel data set including seven periods covering the time period between years 2004 and 2017, where the first time period covers years 2004 and 2005, the second covers 2006 and 2007, up to the seventh time period that covers years 2016 and 2017.

Our dependent variable is the degree of inflation persistence obtained by estimating VARs bi-annually. (as in Equation 1). In terms of its determinants, we try to explain regional and time variation in inflation persistence using the variation in the level of inflation, unemployment, regional per-capita income, trade (as % of GDP), and information on the regional composition of production. For the latter, we control for the percentages of industrial and agricultural production in GDP, separately. We also control for a measure of the size composition of companies in the region, that is, the share of employment in firms with larger than 50 employees. This variable acts as a proxy for the large-firm presence and partially for the degree of competition in the region. This variable is available only for 2002, hence we cannot observe this throughout the panel period. All variables are taken from the Turkish Statistical Institute. Regional per capita income is deflated using regional CPI values with the base year 2003.

For variables used in panel data analysis, descriptive statistics are provided in Table 4, while sample correlations are given in Table 5.

2.3.1 | Multicollinearity

Some of the bilateral correlations in Table 5 appear to be large. In particular, the presence of large firms is highly correlated with per-capita income. These two variables also exhibit a relatively high correlation with variables representing the regional economic structure. In order to circumvent problems regarding potential multicollinearity, we estimate -smaller- specifications in addition to the full

TABLE 4 Descriptive statistics for variables in panel data analysis

Variable	Mean	*SD*	Min	Max
Inflation persistence	−0.3899	0.3854	−1.606	0.4818
Large firms (>49 employees)	0.0044	0.0022	.0017	0.0105
Inflation rate	0.0830	0.0093	0.0572	0.1022
Unemployment rate	10.10	3.974	2.55	27.6
Per-capita ıncome (2003 constant prices)	8032.8	3259.2	2991.2	19825.9
Trade as share of GDP (Openness)	0.1947	0.1863	0.0095	0.7784
Share of İndustry in Regional GDP	0.2746	0.0949	0.0953	0.4928
Share of Agriculture in Regional GDP	0.1534	0.07813	0.0013	0.3496

TABLE 5 Sample correlations for variables in panel data analysis

		Large firms	Inf	Unemp	GDP pc	Trade	Ind.
		1	2	3	4	5	6
Large firms	1	.					
Inflation	2	0.0170	.				
Unemployment	3	0.1807	0.0604	.			
Per-capita ıncome (Regional GDP)	4	0.7998	0.0645	−0.0029	.		
Trade as % of GDP (Openness)	5	0.6760	0.0159	0.3318	0.5540	.	
Share of Industry in Regional GDP	6	0.7394	0.0208	0.2004	0.6061	0.7525	.
Share of Agriculture in Regional GDP	7	−0.7185	−0.0431	−0.2904	−0.6798	−0.6317	−0.4256

model specification. In addition to the full specification (Model 1), our second specification (Model 2) excludes per capita GDP and includes the presence of large firms, inflation, unemployment, shares of trade, industry, and agriculture in GDP. Our third specification (Model 3) excludes trade, industry, agriculture, and share of large firms but includes inflation, unemployment, and GDP per capita as independent variables.

2.3.2 | Persistence of variables and the hybrid panel model

An important issue with our variables is that inflation persistence and some of our independent variables are quite persistent, exhibiting little variation in the within the dimension. This is usual for variables that represent structural properties of the regional economy (openness to trade, shares of industry, agricultural and industrial output in GDP). We also have one variable (share of employment in large firms) for which data are available for only one year. Mixed, or hybrid models that jointly account for the within and between variation in the panel have been developed for such settings (Allison, 2009; Mundlak, 1978; Neuhaus & Kalbfleisch, 1998). Hybrid models decompose all independent variables into the usual within and between components and provide a joint estimate in a random effects specification. This approach also allows the inclusion of time-invariant variables. In our case, we treat the share of large firms (>49 employees) in the region as time-invariant. While we cannot observe changes in this variable over time, we are still interested in the effect of firm size composition at the beginning of the panel period on later outcomes. It is natural and straightforward to introduce a hybrid specification to spatial panel data models, since the former only adds new independent variables to the specification and can be estimated with existing methods.

Mixed models are implementations of the Correlated Random Effects approach in hierarchical or multilevel modeling (Raudenbush & Bryk, 2002; Snijders & Bosker, 2003). Fixed effects methods deal with the issue of correlated effects by removing them entirely, but this data manipulation results in great information loss, which is particularly stringent with persistent variables. Correlated Random Effects models account for the correlation between individual error components by controlling for group-level effects (in our case, region effects). This achieves partial pooling and more efficient use of all sources of variation in data whether within or between units, and clarifies the source of the identifying variation. Bafumi and Gelman (2006) argue that the between components coefficients resolve an important omitted variables problem, and can be interpreted as parameters in and of themselves. Also, see Bell and Jones (2015) for a related discussion and the advantages of mixed models over fixed and random effects models for panel data.

The basic panel data specification we use, without the inclusion of potential spatial effects, can be written as

$$Pers_{it} = \alpha + X^{w}_{it}\beta^{w} + X^{b}_{it}\beta^{b} + \mu_i + \varphi_{it} \tag{4}$$

where $Pers_{it}$ is the *it* (Region *i*, Period *t*) observation for our dependent variable, regional inflation persistence. The disturbance vector consists of an idiosyncratic regional effect (μ_i) which is time-invariant, as well as the usual error term (φ_{it}) that varies across spatial units and time. We introduce a hybrid specification by including within and between components of our independent variables, where X^{b}_{it} and X^{w}_{it} refer to the vectors of independent variables in between and within form, respectively, where $\mathrm{X}^{b}_{it} = \frac{1}{T}\sum_{t=1}^{T} X_{it}$, and $\mathrm{X}^{w}_{it} = X_{it} - \mathrm{X}^{b}_{it}$. Corresponding coefficient vectors are β^{w} and β^{b}. Since one of our variables, the presence of large firms, is available only for 2002, this variable is included in between form alone. All independent variables are used with a logarithmic transformation before between and within components are computed. Regional inflation persistence is used in original form since it assumes negative, as well as positive values.

2.3.3 | Testing for spatial dependence

Since we are dealing with observations that are spatially organized, it is important to control for possible spatial dependencies across regions. Models and estimation procedures for panel data methods that account for spatial error or lag components have been developed (Anselin, 1988; Baltagi et al., 2003; Elhorst, 2014; Kapoor et al., 2007). In what follows, we first establish that our data exhibit spatial dependence that needs to be accounted for. We then move on to determine the most appropriate model to represent spatial effects in the current context.

NUTS-2 regions are likely to be subject to spatial interactions. This is likely to happen through substantial effects among regions via trade and financial linkages, migration, and commuting patterns (Duran & Erdem, 2017; Ertur & Koch, 2007; LeSage & Pace, 2009). So, it is likely that when a region's inflation persistence rises, the increase in persistence might spillover to neighboring regions through input-output relationships, trade, shocks, and other spillover mechanisms.

Indeed, many empirical papers on Turkish NUTS-2 regions, analyzing mostly income or employment, have found spatial dependence evident (Gezici & Hewings, 2007; Yıldırım & Öcal, 2006; Yıldırım et al., 2009). Moreover, the previously performed Moran's I test results in Table 3 indicate the presence of spatiality as well.

To identify the appropriate spatial model, we apply panel spatial autocorrelation and cross-sectional dependence tests to our empirical model (without any fixed/random effect). LM test for spatial error and lag dependence is applied to examine the null hypothesis of no spatial dependence in error terms or dependent variable, respectively, (Anselin, 1988, 2001; Anselin et al., 1996, 2008; Anselin & Moreno, 2003; Anselin & Rey, 1991; Baltagi et al., 2003, 2012; Bera et al., 2019; Millo & Piras, 2012). Pesaran CD and Breusch-Pagan LM tests are implemented to examine the cross-sectional dependence in panels. (Baltagi et al., 2012; Breusch & Pagan, 1980; Jarque & Bera, 1980; Millo & Piras, 2012; Pesaran, 2004; Pesaran & Tosetti, 2011). Specifically, they test the null hypothesis of the absence of cross-sectional dependence against spatial dependence.

Then, few more tests are applied to the following hybrid panel model to understand whether spatial autocorrelation and/or random effects are present. Tests presented in the last three rows of Table 6 are applied to the Hybrid model. For instance, Baltagi et al. (2003)'s LM-H one-sided joint test is used to examine the null hypothesis of no Random Regional Effects and Spatial autocorrelation, their LM2 marginal test and lambda conditional LM test are used to understand the null hypothesis of the absence of spatial autocorrelation.

Regarding the results of LM tests (presented in the first two rows), the results in Table 6 indicate quite strong spatial autocorrelation since the test statistics are statistically significant always at 1%. Moreover, cross-sectional dependence tests are also statistically significant as presented in the 3rd and 4th rows. The last three tests of Baltagi et al. (2003) indicate the spatial autocorrelation as well. Hence, it is understood that the most general spatial models are more appropriate such as Spatial Durbin Model (Durbin, 1960). SAR and SEM models should also be incorporated for the sake of robustness and completeness. Model selection is discussed and justified in detail in the next sub-section.

TABLE 6 Panel spatial autocorrelation and cross-sectional dependence tests

Test type	Test statistic	*p* value
LM test for spatial error dependence	36.613***	1.44E−09
LM test for spatial lag dependence	36.426***	1.59E−09
Pesaran CD test for cross-sectional dependence in panels	10.383***	<2.2e−16
Breusch-Pagan LM test for cross-sectional dependence in panels	463.07***	7.13E−07
Baltagi, Song, and Koh LM-H one-sided joint test	280.13***	<2.2e−16
Baltagi, Song,, and Koh LM2 marginal test	16.737***	<2.2e−16
Baltagi, Song, and Koh LM-lambda conditional LM test	55.036***	3.72E−05

***Statistical significance at 1%;

**Statistical significance at 5%;

*Statistical significance at 10%.

2.3.4 | Spatial model selection

In order to identify the most appropriate representation of spatial dependence in the current context, we follow the existing literature on model selection for spatial dependencies. We begin by the model selection procedure suggested by Elhorst (2010), who propose beginning with the Spatial Durbin Model (SDM), which includes a spatial autocorrelation variable as well as spatial lags of independent variables.

$$Pers_{it} = \alpha + \rho \sum_{j=1}^{N} W_{ij} Pers_{jt} + X_{it}\beta + \sum_{j=1}^{N} W_{ij} X_{jt}\theta + \mu_i + \varphi_{it} \tag{5}$$

In addition to Equation (4), W_{ij} refers to the ij component of the 26×26 spatial contiguity matrix W, which is calculated using queen contiguity with 10 km. precision and is in row-standardized form. Parameter ρ is the spatial autoregressive component, while β and θ are vectors of coefficients for independent variables and their spatial lags, respectively.

The SDM specification generalizes both the Spatial Autoregressive Model (SAR) and the Spatial Error Model (SEM). Hence, the model can be used to perform hypothesis tests to select among nested models. The hypotheses $H_0: \theta = 0$ and $\tilde{H}_0: \theta + \rho\beta = 0$ are tested in order to determine whether the SDM can be reduced to the SAR (if H_0 is rejected) or SEM (if $\tilde{H}_0$ is rejected) models (Elhorst, 2010; LeSage & Pace, 2009, 2014). If both are rejected, then SDM is the best specification. We perform both tests on random effect and hybrid panel model specifications and present the results in Table 7. Both hypotheses conduct nested model selection which is in the form of likelihood ratio (LR) tests, and both follow chi-squared distribution, the degrees of freedom of which equals the difference in the number of parameters between the unrestricted (SDM) and restricted (SAR or SEM) models.

With regard to the detailed results of this test, we find that neither H_0 nor $\tilde{H}_0$ can be rejected, which may suggest that either the SAR or the SEM model can account for spatial dependency in our model. However, a literal reading of the test results could lead to the interpretation that no spatial modeling is required. We note that the alternative hypothesis in both tests is the SDM model, hence each test is conducted conditional on the other being false. To investigate this issue fully, we also conduct a joint test of both hypotheses, that is, $\overline{H}_0: \theta = 0\ and \theta + \rho\beta = 0$. This joint hypothesis is strongly rejected by

TABLE 7 Tests for model selection based on the spatial Durbin model

	Likelihood ratio (χ^2) test statistics	
Null hypothesis (Model)	**Random effects**	**Hybrid effects**
$H_0: \theta = 0$	6.542 (7, 14.07)	14.754 (13, 22.36)
	Not rejected	Not rejected
$\tilde{H}_0: \theta + \rho\beta = 0$	5.060 (7, 14.07)	11.582 (13, 22.36)
	Not rejected	Not rejected
$\overline{H}_0: \{\theta = 0\ and \theta + \rho\beta = 0\}$ (No Spatial Effect)	37.202 (8, 15.51)	46.376 (14, 23.69)
	Rejected	Rejected

Note: Chi-square degrees of freedom and the corresponding 5% critical values are in parenthesis.

our data. We conclude that the structure of spatial dependence in our data is such that *either* the SEM or the SAR specification can account for spatial dependence, since controlling either for a spatial autoregressive lag, or spatial error dependence leaves little additional spatial effects to be explained. This observation, along with the rejection of the joint statistics clearly indicate that the more general Spatial Durbin Model should be adopted.

A problem with the SDM model is that including the complete list of spatial lags to the model introduces strong multi-collinearity, especially, but not restricted to, in the hybrid model specification.[3] As a result, it is not possible to include the spatial lags of all independent variables in the final model. As a solution, we adopt a partially restricted SDM model with the inclusion of the spatial lags for a selected subset of independent variables, in addition to the spatial autoregressive term. The same is proposed by Elhorst (2010) in a similar context. We begin by choosing the spatial lags that do not exhibit very high correlations with other variables. As a result, we include spatial lags of trade (openness), industry share, and agriculture share in their between forms. Note that within variables did not produce any significant coefficients in SDM specifications that exclude highly correlated variables.

We also note that the SAR model is usually preferred in case of a difficult choice This is because the cost of misspecification is higher if the true model is SAR, as this renders remaining coefficients biased and inconsistent. In contrast, excluding spatial error dependence affects standard errors, and leads to efficiency losses (Elhorst, 2010; LeSage & Pace, 2009, 2014). Given the existing issues in model selection, we also estimate SAR and SEM models as useful robustness checks with respect to alternative specifications (see for the detailed background of SAR, SEM, SDM models; Anselin, 1988; Anselin et al. 2008; Baltagi et al. 2003, 2007, 2012; Durbin, 1960, Elhorst, 2010, 2014; Millo & Piras, 2012).

Therefore, our final specification can be expressed in SDM form

$$Pers_{it} = \rho \sum_{j=1}^{N} W_{ij} Pers_{jt} + X_{it}^{w} \beta^{w} + X_{it}^{b} \beta^{b} + \sum_{j=1}^{N} W_{ij} \tilde{X}_{it}^{b} \theta + \mu_i + \varphi_{it} \quad (6)$$

which is similar to Equation (5), except that $\tilde{X}$ refers to the subset of variables whose spatial lags are included in the specification.

The SAR model specification takes a similar form, except it takes $\theta = 0$, while the SEM specification assumes $\rho = \theta = 0$ with the additional error specification

$$\varphi_{it} = \delta \sum_{j=1}^{N} W_{ij} \varphi_{jt} \quad (7)$$

While the hybrid effect methodology does not require rejecting the randomness of individual effects, we also report that the spatial Hausman test (Mutl and Pfaffermayr, 2011) cannot reject the null that individual effects are random given the presence of spatial error autocorrelation ($h = 0.865$ (χ^2_7), p value = .996).

2.3.5 | Regression results

Table 8 reports result from hybrid panel specifications with inflation persistence as the dependent variable. Columns 1–3 reports results using the full specification, while columns 4–6 and 7–8 report

TABLE 8 Regional determinants of inflation persistence: hybrid-effects spatial Durbin (SDM), SAR, and SEM models

		Model 1			Model 2			Model 3	
		All variables							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		SDM	SAR	SEM	SDM	SAR	SEM	SAR	SEM
Large firms	(B)	−0.2819*	−0.2429*	−0.2504*	−0.2792**	−0.1576	−0.2088*		
(>49 employees)		(0.1570)	(0.1478)	(0.1325)	(0.1374)	(0.1229)	(0.1182)		
Inflation	(W)	−0.1244	−0.1233	−0.4210	−0.1202	−0.1176	−0.3646	−0.1247	−0.4178
		(0.2250)	(0.2274)	(0.3260)	(0.2256)	(0.2288)	(0.3248)	(0.2307)	(0.3309)
	(B)	1.6296	1.6748	1.3416	1.6229	1.5971	1.2655	1.6282	1.6352
		(1.2428)	(1.2151)	(1.0546)	(1.2309)	(1.2209)	(1.0578)	(1.2381)	(1.1334)
Unemployment	(W)	0.1589	0.1590	0.1658	0.1492	0.1495	0.1558	0.18024	0.1705
		(0.1208)	(0.1221)	(0.1286)	(0.1208)	(0.1226)	(0.1293)	(0.1242)	(0.1298)
	(B)	−0.0760	−0.0039	−0.0312	−0.0773	−0.0332	−0.0398	−0.0023	−0.0419
		(0.0995)	(0.0914)	(0.1044)	(0.0928)	(0.0874)	(0.1040)	(0.0775)	(0.0955)
Per-capita Income	(W)	0.3330	0.3336	0.5355				0.2204	0.4152
		(0.3171)	(0.3205)	(0.3909)				(0.1867)	(0.3275)
	(B)	0.0066	0.1410	0.1069				0.0671	0.1144
		(0.1816)	(0.1383)	(0.1632)				(0.0681)	(0.1005
Trade in GDP (Openness)	(W)	0.2127*	0.2133*	0.1948	0.2441**	0.2455**	0.2320*		
		(0.1250)	(0.1263)	(0.1291)	(0.1217)	(0.1235)	(0.1273)		
	(B)	−0.0981*	−0.1007**	−0.1210**	−0.0981*	−0.1011**	−0.1283***		
		(0.0515)	(0.0474)	(0.0490)	(0.0516)	(0.0477)	(0.0479)		
Spatial Lag	(L-B)	0.3506*	0.3541**						
		(0.1904)	(0.1659)						

(Continues)

TABLE 8 (Continued)

		Model 1			Model 2			Model 3	
		All variables							
		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		SDM	SAR	SEM	SDM	SAR	SEM	SAR	SEM
Share of Industry in GDP	(W)	−0.3795	−0.3796	−0.3254	−0.1923	−0.1918	−0.1977		
		(0.3709)	(0.3749)	(0.3704)	(0.3262)	(0.3309)	(0.3611)		
	(B)	0.3057*	0.2760*	0.3659**	0.3053*	0.2701*	0.3740**		
		(0.1822)	(0.1624)	(0.1652)	(0.1819)	(0.1634)	(0.1657)		
Spatial Lag	(L-B)	−0.7660*			−0.7697*				
		(0.4224)			(0.4112)				
Share of Agriculture in GDP	(W)	0.1062	0.1069	0.1792	−0.0199	−0.0189	0.0249		
		(0.2308)	(0.2332)	(0.2886)	(0.1977)	(0.2005)	(0.2668)		
	(B)	−0.1944***	−0.1041**	−0.1234**	−0.1953**	−0.1156**	−0.1389***		
		(0.0673)	(0.0481)	(0.0517)	(0.0627)	(0.0470)	(0.0460)		
Spatial Lag	(L-B)	0.0868			0.0880				
		(0.0808)			(0.0754)				
Constant		2.1100	1.3083	0.6534	2.1737	2.8748	1.6285	3.2558	2.7543
		(3.4458)	(3.3808)	(3.0911)	(3.010)	(3.0266)	(2.7395)	(3.1807)	(2.9565)
rho (Spatial Autoregressive Coefficient)		0.4764***	0.4713***		0.4776***	0.4664***		0.4655***	
		(0.0744)	(0.0748)		(0.000)	(0.0750)		(0.0757)	
delta (Spatial Error Coefficient)				0.5157***			0.5081***		0.5040***
				(0.0768)			(0.0772)		(0.0802)

Note: (W) refers to within, and (B) to between level variables. (L-) refers to the spatial lag of the variable in the preceding column. Number of observations = 182 (26 regions, 7 time periods between 2004 and 2017). Standard errors are shown in parentheses.

***Significance at 1%; **Significance at 5%; *Significance at 10%.

results using smaller specifications that guard against multicollinearity. Our preferred specifications are the SDM specifications for each model, while the rest provide robustness checks. All coefficients are semi-elasticities, as all variables except persistence are used in log transformation. As expected, the within dimension does not contain much variation, and provides insignificant results for all but one variable. The between-region variation exhibits an interesting association with inflation persistence.

With regard to the results, large firms share (−), trade (+ within, − between), industry share (+), and agriculture share (−) have significant impacts on regional inflation persistence. The results are consistent across all the methods and specifications. The presence of large firms affects inflation persistence negatively, which is an effect that is significant at 10% for most specifications, and 5% in our preferred specification for Model 2. We find that the composition of production is associated with inflation persistence across regions. Persistence increases with the share of industry in regional output, while it falls with the share of agriculture. The coefficient of trade is positive in the within, but negative in the between dimension. We do not find any other covariates to exhibit a statistically significant association with inflation persistence.

In all specifications in which they are included, spatial autoregressive or error components are positive and significant. This indicates the fact that inflation persistence is spatially clustered. In other words, an increase in inflation persistence spills over to neighbor regions. This may happen through linkages of trade, input-output relationships, commuting patterns, or shocks.

Our partial SDM model, as well as SAR models, can produce overall direct and indirect effects that are different than implied by coefficient estimates. In order to obtain sharper inference, we also obtain the direct and indirect effects due to each variable. For this purpose, we use the procedure suggested and described by Elhorst (2010), using 1,000 simulated values of said effects using coefficient estimates and their variance-covariance matrix. Table 9 reports direct and indirect effect estimates using the specification in column 4 of Table 8. The sign and significance of the direct and indirect effects are quite consistent with the coefficient estimates in Table 8, with some key differences.

Our dual finding that the share of agriculture (industry) in regional GDP leads to lower (higher) inflation persistence is meaningful and in line with expectations, since agricultural sectors are known to be prone to high price volatility. Regions with a higher share of industrial output face higher persistence, which indicates that regional industrialization safeguards the region against price volatility and establishes stability. The spatial lag of the industry variable has a negative and significant coefficient.

However, our results emphasize the importance of obtaining direct and indirect impact estimates for estimating spillover effects. These impacts are results of a network of spatial interactions, of which the spatial lag coefficient is only one component, and one that is conditional on other variables in the model.

The direct effect estimate in Table 9 implies that the overall spillover effect of the industry variable is positive. Industrialization in surrounding regions increases inflation persistence in a region substantially. Spatial spillover mechanism through economic linkages plays an important role. It is worth noting that the overall indirect effect is larger than the direct effect for this variable.

The direct effect of agriculture share in Table 9 is consistent with the coefficient estimates in Table 8. Similar to the industry variable, the indirect impact is larger for agriculture as well. Agricultural specialization in neighboring regions decreases the inflation persistence of a region via spatial linkages.

The effect of trade is positive in the within, but negative in the between dimension in Table 8. This indicates that increased openness has a positive effect in the short run, for a given region. However, across regions, those that are more open may be experiencing lower persistence compared to others. This indicates an effect through which open regions obtain a less stable inflation regime compared to closed ones, perhaps through higher vulnerability against international competition, global shocks, as

TABLE 9 Direct and indirect effects

		Direct effect	Indirect effect
Large firms (>49 employees)	(B)	−0.3041**	−0.2500*
		(0.1489)	(0.1429)
Inflation	(W)	−0.1347	−0.1101
		(0.2503)	(0.2189)
	(B)	1.7631	1.4505
		(1.3252)	(1.2511)
Unemployment	(W)	0.1623	0.1335
		(0.1274)	(0.1144)
	(B)	−0.0913	−0.0744
		(0.0967)	(0.0858)
Trade in GDP (Openness)	(W)	0.2651**	0.2181*
		(0.1295)	(0.1315)
	(B)	−0.0509	0.5540*
		(0.0634)	(0.3238)
Share of Industry in GDP	(W)	−0.1864	−0.1563
		(0.3337)	(0.3025)
	(B)	0.3960**	0.9206**
		(0.1917)	(0.4007)
Share of Agriculture in GDP	(W)	−0.0110	−0.0099
		(0.2165)	(0.1889)
	(B)	−0.3360***	−1.5892*
		(0.1271)	(0.8467)

Note: Direct and indirect effects are calculated using estimation results presented in column 4 of Table 8. (W) refers to within, and (B) to between level variables. Number of simulations = 1,000. Standard errors are expressed in parentheses. The effects are computed in the R programming language.

***Significance at 1%; **significance at 5%; *significance at 10%.

well as against exchange rate movements. However, the spatial lag of the trade variable has a positive and significant coefficient, indicating a positive effect of having more open neighbors on inflation persistence. The indirect effect estimate in Table 9 suggests that this latter effect dominates, and produces a large and positive effect of having trade intensive neighbors on inflation persistence.

Our result that the presence of large firms in the region affects inflation persistence negatively is also interesting. It is likely that this variable, indeed, acts as a proxy for higher market concentration (less competition) in the regional economy, and is due to the higher market power of such firms that destabilizes prices compared to regional economies consisting of small firms to a larger extent. Also note that this effect is unlikely to be due to differences in development or industrialization across regions, since we control for these attributes directly. The direct and indirect effect of the presence of large firms seem to have a similar magnitude.

It is important to note that neither regional income (per-capita GDP), inflation nor the level of regional unemployment have significant effects on the persistence of inflation across Turkish regions.

While both variables have been theoretically linked to inflation persistence, they do not appear to be empirically important determinants of inflation persistence in Turkish regions.

Our results also suggest that direct and indirect effects should be separately evaluated as indirect effects and related spatial spillover mechanisms are quite influential on inflation persistence.

3 | CONCLUSIONS AND DISCUSSION

In this study, we investigated the degree of inflation persistence in Turkish regions over the period 2003M1-2019M4. In detail, the geographical distribution of inflation persistence and robustness of the pattern with respect to structural breaks and nonlinearities is estimated. The possibility of geographical/sectoral aggregation bias and, finally, the sources of cross-regional variation in persistence also are explored. A quite broad range of time series methods and panel data models were applied.

As a result, three groups of results are obtained. First, estimated persistence degrees are heterogeneous across regions, ranging between 0.36 and 0.003. The estimated geographical pattern is empirically robust against structural breaks, possible nonlinearities, and the choice of lag length.

A spatial pattern in inflation persistence is found. This spatiality was tested and found evident by the help of Moran's I test, LM, and LR spatial specification tests. The zone between Istanbul and Ankara, Eastern/Northeastern Anatolian regions, Aegean/Mediterranean west coast from Aydın to Antalya has relatively more persistent prices. In contrast, some Northwestern regions (TR21, TR22), some Southern (TR62, TRC1), and Black Sea regions (TR83) have the least persistence. Therefore, special policy programs targeted at maintaining price flexibility in the regions are required where persistence is high. These programs might be in a heterodox and reformist manner. They should be aiming at changing the market structure and enable price flexibility. Policy credibility, institutional quality, and transparency are among the necessary steps. Structural reforms that support free exit/entry of firms to the market, regulations that promote competition, and other conventional subsidization tools such as the encouragement of SMEs, rental aid, tax exemptions are among the possible policies that might be applied to these regions.

Second, when sectoral and regional aggregation bias is tested, it is seen that no bias is observed for geographical aggregation but the sectoral aggregation indicates the considerable level. Therefore, sectors that have high persistence, such as Hotels and Restaurant (persistence degree: 0.55), Health Services (0.39), Furniture (0.33), should be given more weight in CPI calculation. Failing to do so might create sizable deviations from optimal monetary policy.

Third, by employing spatial panel data regressions, we have identified several variables and regional attributes that determine inflation persistence in Turkey. Our results indicate that a higher degree of industrialization leads to higher inflation persistence. Regions that have increased trade openness also experience higher inflation persistence. Moreover, inflation is less persistent in regions that have higher orientation toward agriculture, and which contains a larger share of large (>49 employees) firms. We document substantial spillover effects. The indirect effect of our key variables (particularly, industry, agriculture, and trade) were found to be more sizable compared to the direct effect, possible driven by spatial spillover mechanisms. Another important finding is that inflation persistence is not affected by the levels of regional unemployment, inflation or income in Turkey.

In sum, policy makers should consider all these facts with great care to be able to stick to the inflation targets and achievement of price stabilization.

DATA AVAILABILITY STATEMENT

The dataset used in this paper is available upon request.

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ENDNOTES

[1] We use the "splm" and "spdep" packages written in statistical computing language R (Bivand et al. 2019; Millo & Piras, 2012) to estimate our specifications. EViews 4, Eviews 10, and STATA 13 are also used in the empirical analysis.

[2] More technical details can be found at https://www3.nd.edu/~nmark/FinancialEconometrics/EViews10_Manuals/EViews-%20Users%20Guide%20II.pdf

[3] The correlation matrix that includes all within and between variables, as well as their spatial lags, is available from the authors upon request. High correlations (> 0.8) exist among variables and their spatial lags, including inflation (within), GDP per capita (both), trade share (between), agriculture share (within), among others.

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