



Relative price variability and inflation: New evidence☆☆☆



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ABSTRACT

This paper investigates the relationship between relative price variability (RPV) and inflation using monthly micro-price data for 128 goods in 13 Turkish regions/cities for the period 1994–2010. The unique feature of this data set is the inclusion of annual inflation rates ranging between 0% and 90%. Semi-parametric estimations show that there is a hump-shaped relationship between RPV and inflation, where the maximum RPV is achieved when annual inflation is approximately 20%. It is shown that this result is consistent with a region- or city-level homogenous menu cost model that features Calvo pricing with an endogenous contract structure and non-zero steady-state inflation.

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1. Introduction

Given the implications for the welfare cost of inflation and monetary neutrality, the relationship between inflation and relative price variability (RPV) has long been debated in the literature. Although theoretical models have generally predicted a positive relationship,¹ the direction and functional form of this linkage have not always been verified by empirical studies. Despite the existence of a large body of empirical studies reporting a positive relationship,² a number of studies have supported a reverse relation between RPV and inflation.³ Reinsdorf (1994) found that this relationship is negative during the 1980s for the U.S. (Fielding and Mizen, 2000), and Silver and Ioannidis (2001) reported the same result for several European countries.

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¹ Whereas menu cost or Lucas-type confusion models predict linear and positive associations between inflation and RPV, recent monetary search and Calvo-type models (see Head and Kumar, 2005; Choi, 2010) predict an inflation–RPV nexus with a U-shaped form.

² See Van Hoomissen (1988), Lach and Tsiddon (1992), Parsley (1996), Dabús (2000), Kucuk-Tuger, Tuger, (2004), and Lastrapes (2006), among others. More recently, Ukoha et al. (2007) find that inflation has a significant positive impact on RPV among agricultural commodities in Nigeria, and Gerling and Fernandez Valdovinos (2011) document a positive relationship for eight countries from the West African Economic and Monetary Union.

³ In addition to the detailed literature review provided here, a brief summary of empirical studies on the inflation–RPV nexus is given in the Appendix in Table A1.

Starting with the work of Parks (1978), who first noted that RPV increases more during periods of price decreases than during periods of price increases, the asymmetric or generally nonlinear effects of RPV on inflation have attracted some attention in the literature. This new direction of research has questioned the underlying functional form of the relationship and has provided evidence of a quadratic relationship or threshold effects. The evidence of threshold effects differs somewhat by countries, depending on the nature of the inflation–RPV nexus. Jaramillo (1999) showed that in the U.S., the impact of inflation on RPV, though it is always positive, is stronger when it is below zero. Similarly, Caraballo et al. (2006) report that for Spain and Argentina, the positive effect is stronger when inflation is high and exploded during the hyperinflationary period in Argentina. Using data from Turkey, Caglayan and Filiztekin (2003) also showed that the association is significantly different during low and high inflation periods. Contrary to these aforementioned studies, during highly inflationary episodes, the association between inflation and inflation variability is significantly lower. However, Bick and Nautz (2008) found that for the U.S., both positive and negative effects of inflation on RPV are observed in the sense that inflation increases RPV only if it exceeds a threshold value. The results for the Euro area presented by Nautz and Scharff (2012) indicate that inflation significantly increases RPV only if inflation is either very low or very high in the range of their sample values.⁴ More recently, conformable with recent monetary search and Calvo-type model predictions (see Head and Kumar, 2005; Choi, 2010), evidence has been provided of a U-shaped relationship between inflation and RPV by Choi (2010) for the U.S. and Japan; Choi and Kim (2010) for the U.S., Canada and Japan; Becker (2011) for a panel of European countries; and Fielding and Mizen (2008) for the U.S.⁵ Moreover, in a more recent study of the effect of inflation targeting (IT) on the inflation–RPV nexus, Choi et al. (2011) analyzed a data set of twenty industrial and developing countries consisting of 12 targeters and eight non-targeters, including Turkey, during the so-called great moderation period. They show that the underlying relationship between inflation and RPV is U-shaped in most cases under study, in line with the findings by Choi and Kim (2010) and Fielding and Mizen (2008).⁶

In this paper, we contribute to the existing literature by estimating the relationship between RPV and inflation using a semi-parametric method that allows us to estimate varying coefficients capturing changing effects of inflation, if they exist, on RPV at different levels of inflation. In this respect, we use an estimation method similar to those of Choi (2010), Choi and Kim (2010), Choi et al. (2011) and Fielding and Mizen (2008) in a panel data context by introducing further regional dimensions in addition to goods levels. This unique data set covers quite a large range of (annual) inflation levels varying from 0% to 90%. In our opinion, this specific feature of the data constitutes an important opportunity to examine the inflation–RPV nexus in different inflationary environments.⁷

The empirical evidence provided clearly indicates the fact that the relationship between RPV and inflation is nonlinear and varies significantly with the level of inflation. However, unlike the previous studies, our empirical evidence indicates a hump-shaped relation between inflation and RPV, where the maximum dispersion is achieved when annual inflation is approximately 20%. We show that this result is consistent with a region- or city-level homogeneous menu cost model. This homogeneous menu cost model features Calvo pricing with an endogenous contract structure and non-zero steady-state inflation, where the Calvo parameter is determined through optimization. This model is capable of generating a hump-shaped relation between RPV and inflation and significantly differs from the model of Choi (2010), which produces a U-shaped relationship. Choi (2010)'s model, unlike ours, uses sectoral heterogeneity in an exogenous contract setting in which the Calvo parameter is determined in an ad-hoc manner and is assumed to differ across sectors.⁸ The existing literature has also distinguished between the effects of anticipated and unanticipated components of inflation on RPV, although the evidence is mixed. The corresponding theoretical literature includes studies such as those by Lucas (1972) predicting a non-negative relationship between RPV and the absolute value of unanticipated inflation, as well as studies such as by Rotemberg (1983) and Head and Kumar (2005), who predict a U-shaped relationship between anticipated inflation and RPV. The corresponding empirical literature includes studies finding a convex relationship between RPV and unanticipated inflation (e.g., see Parks, 1978; Hesselman, 1983; Glezakos and Nugent, 1986), as well other studies focusing on linear in anticipated inflation and V-shaped in unanticipated inflation (e.g., see Lach and Tsiddon, 1992) versus studies focusing on quadratic in anticipated and unanticipated inflation (e.g., see Aarstol, 1999; Becker and Nautz, 2009). Therefore, the consideration of the anticipated versus unanticipated components of inflation has been shown to be important in the literature.

⁴ In their studies, a very low level of inflation refers to a per annum rate below 0.95%, and a very high level is 4.96%. As we will see below, in our samples, both of these rates are considered low inflation because our study includes inflation rates up to 90%.

⁵ Similarly, Akmal (2011) showed a U-shaped relationship for Pakistan, and Ndou and Redford (2014) showed another U-shaped relationship for South Africa. Further, Tommasi (1992), Debelle and Lamont (1996) and Caglayan et al. (2008) reported a symmetric V-shaped relationship between inflation and RPV.

⁶ They also reported that while the U-shaped profile is found among low-inflation countries regardless of IT adoption, it is observed among high-inflation targeters only after IT adoption. However, no such shift to a U-shaped relationship is observed among the high-inflation non-targeters studied, including Turkey. Although Turkey adopted explicit IT in January 2006, it is classified as a non-targeter in the study by Choi et al. (2011) because it was a non-targeter for most of the sample period. As a non-targeter, the break date for the decrease in inflation is February 2002, which is consistent with our data. Note that Turkey pursued implicit IT during the period 2002–2005 (see Kara, 2012). We discuss their results for Turkey further in Section 2.2 below.

⁷ Only a few previous studies covered such high rates of inflation along with considerably lower values. In this regard, Choi et al. (2011) constitutes the main exception together with Caraballo et al. (2006) and Caglayan and Filiztekin (2003).

⁸ Choi (2010) notes that the shape of the inflation–RPV nexus depends on the average degree of price rigidity. For sectors in which the average degree of price rigidity is high, the relationship is U-shaped, but this link weakens when price adjustment is highly flexible (see Becker, 2011).

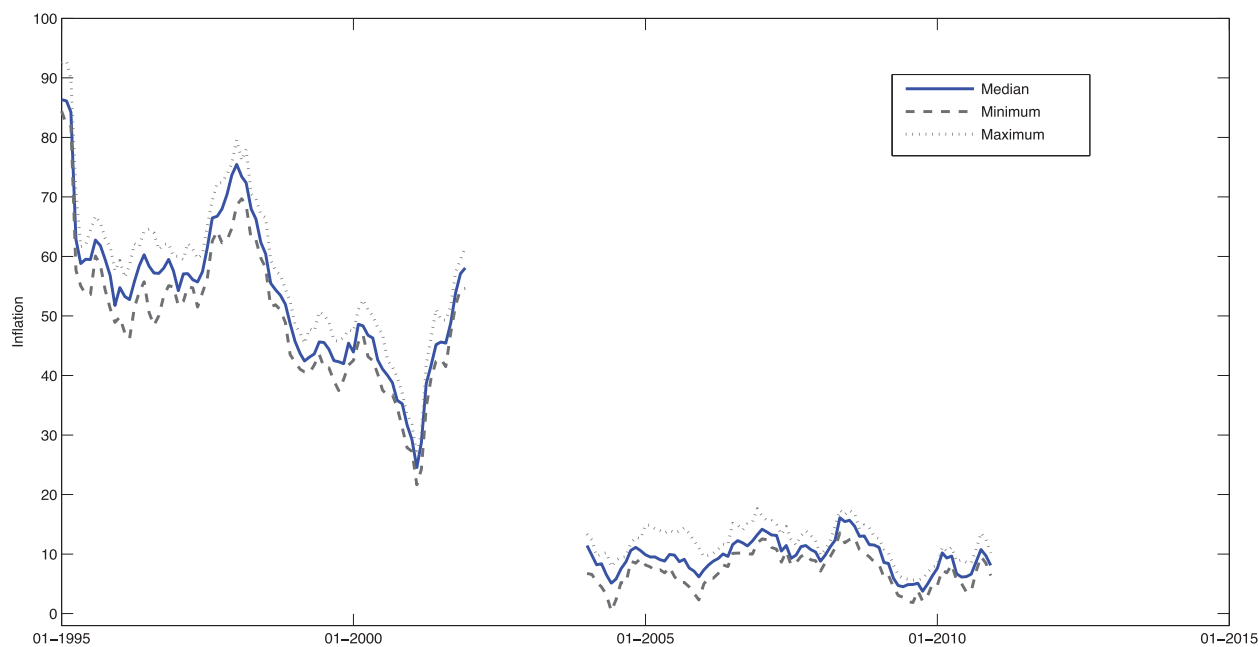


Fig. 1. Inflation rates across the cities in Turkey. Notes: Minimum (dashed line), median (solid line), and maximum (dotted line) of annual inflation for 13 cities in Turkey for 1995:M1–2001:M12 and 2004:M1–2010:M12.

Within this picture, for the robustness of our results introduced above, we also consider anticipated versus unanticipated components on inflation in our estimations. Because the estimation of the smoothing parameter (bandwidth) is crucial in any semi-parametric analysis, we also consider alternative smoothing parameters in our semi-parametric estimations. Further, because Turkey has gone through many business cycles during our sample period, in alternative specifications, we further controlled for the fluctuations in our data due to business cycles. In all of these robustness checks, the results showed that the hump-shaped relationship between inflation and RPV remains the same. In the following sections, we present our data and estimation results. After presenting the model, we go over the details of our robustness checks and conclude.

2. Data and estimation

Our empirical analysis uses the monthly price data of the 128 seasonally adjusted good-level prices published by the Turkish Statistical Institute (TurkStat) for a panel of 13 cities from January (M1) 1994 to December (M12) 2001 and from 2003:M1 to 2010:M12.⁹ We compute the annual inflation for each month, with respect to the corresponding month from the previous year, and year over year (yoy) inflation rates for each month, starting in 1995:M1 and 2004:M1. Therefore, we have a data set covering the period 1995:M1–2010:M12 with a two-year gap for 2002 M1–2003 M12. Due to this discontinuity in our data, we conduct two separate estimations for the periods 1995:M1–2001:M12 and 2004:M1–2010:M12. One important feature of these data is that the inflation levels of these two periods do not overlap. In other words, the high-inflation period's rates never reach levels as low as those observed during the low-inflation period. The time-varying nature of our estimation procedure and this feature of the data help to justify the interpretation of the results of these two separate estimations as a single entity (see Section 2.2 below).¹⁰

Fig. 1 displays the median, minimum and maximum city-specific inflation rates calculated as the good-level averages with appropriate weights for two periods of Turkish inflation. Between 1995:M1 and 2001:M12, inflation exceeds 90% in some cities but approaches 25% in others. During this first era, median inflation is unstable and fluctuates around 54%. However, during the period 2004:M1–2010:M12, the inflation rates are as high as 18% in some cities and approach zero in others. The median inflation rate remains as low as 10% during this period.

⁹ Detailed descriptions of our good-level price data are given in Appendix A.

¹⁰ Because our work uses data on the same country, we should compare our data to those of Caglayan and Filiztekin (2003), Caglayan et al. (2008) and Choi et al. (2011). Caglayan et al. (2008)'s data consist of monthly price observations for 58 individual products sold by individual sellers in 15 neighborhoods (boroughs) in Istanbul during the period 1992:M10–2000:M6 when the average inflation rate was high but relatively stable at approximately 60% per annum. Caglayan and Filiztekin (2003), however, use long-term disaggregated annual price data for 22 food products collected from the 19 largest provinces in Turkey over the period 1948–1997. Choi et al. (2011) cover the period 1986:M1–2009:M9 for 5 different products.

We follow the empirical literature and measure the RPV as

$$RPV_{i,t} = \sqrt{\sum_{j=1}^{128} \omega_j (\pi_{ij,t} - \pi_{i,t})^2}, \quad (1)$$

where i and t refer to city and time indexes such that $i = 1, \dots, N = 13$ at time $t = 1, \dots, T = 84$ for both data sets. π denotes the yoy annual inflation rate for good $j = 1, \dots, 128$, calculated as $\pi_{ij,t} = \ln P_{j,t} - \ln P_{j,t-12}$, where $P_{j,t}$ is the corresponding price level, $\pi_{i,t} = \sum_{j=1}^{128} \omega_j \pi_{ij,t}$ denotes the inflation rate for city i at period t , and the weight of the j th good is denoted by ω_j such that $\sum_{j=1}^{128} \omega_j = 1$.¹¹

Following the terminology introduced by Lach and Tsiddon (1992), this measure of RPV is referred to as the intermarket RPV, where the relevant concept is the dispersion of the product inflation rates around an aggregate rate of inflation in a given city. An alternative measure would be intramarket RPV, which can be defined as the variability of relative prices of a given product across cities or stores. The empirical literature uses either intermarket or intramarket measures of RPV depending on data availability or, if possible, considers both measures simultaneously.¹² In the theoretical model presented in Section 3, RPV is defined as the intermarket RPV; hence, we use the RPV of Eq. (1) in our empirical model.

2.1. Empirical model

In this section, we investigate the relationship between RPV and inflation using a semi-parametric model. As is widely accepted, the functional form of the relationship between variables is generally unknown, and parametric models are only implemented due to their simple estimation procedures and ease of interpretation. However, the shape of the relationship between the variables could be highly complicated, and a parametric model may present a deceptive picture of this relationship. To avoid the potential disadvantages of adopting a parametric model, we utilize a semi-parametric approach, which consists of a combination of parametric and nonparametric models. Semi-parametric estimation procedures are appealing because they preserve both the simplicity of parametric and the flexibility of nonparametric models. They are also more informative than their alternatives, such as threshold models, which impose a piecewise linear structure on the inflation function.

Specifically, we consider a partially linear regression model in which inflation has an unknown functional form and other regressors enter the model linearly. Hence, we estimate the following partially linear panel data model:

$$RPV_{i,t} = \alpha_i + x'_{i,t} \gamma + m(\pi_{i,t}) + u_{i,t}, \quad (2)$$

where $m(\cdot)$ refers to the unknown smooth function that determines the underlying functional form of the relationship between inflation and RPV. The $r+k$ vector of regressors x include the lagged terms of RPV and π , in particular $x'_{i,t} = \{RPV_{i,t-1}, \dots, RPV_{i,t-r}, \pi_{i,t-1}, \dots, \pi_{i,t-k}\}$. Finally, the α_i 's capture the city-specific individual fixed effects. We estimate the unknown function $m(\cdot)$ and γ with the profile least squares of Su and Ullah (2006).¹³ The procedure provides a coefficient estimate for each observation of inflation in our sample. We have a balanced panel of 13 cities for 84 months, and hence, 1092 observations for yearly inflation rates for each period for which we perform the estimation.¹⁴

Because asymptotic normality approximation may perform badly for both the distribution of estimated parameters and the nonparametric component in finite samples, proper inference is assured by employing a fixed-design wild bootstrap procedure, which is also robust to the presence of cross-sectional and temporal clustering of the residuals.¹⁵ Further technical details of the econometric methodology are given in Appendix B.

2.2. Results

Table 1 reports the coefficient estimates and bootstrap confidence intervals (at 95% level) for the control variables that enter the model linearly. Panels A and B demonstrate our findings for the initial period and recent sample periods of

¹¹ The weights are taken from TurkStat.

¹² Reinsdorf (1994) states that the theoretical literature refers specifically to relative price-level variability rather than the relative price-change (inflation) variability as defined in (1). These two dispersion measures are not equivalent and can have different relationships with inflation. However, Reinsdorf's statement refers to intramarket RPV rather than intermarket RPV, for which the relevant measure should be changes rather than levels.

¹³ We use the Gaussian kernel function and smoothing parameter h based on the normal reference rule-of-thumb. We also implement a least squares cross-validation approach and Hurvich et al. (1998)'s expected Kullback–Leibler criteria to check the sensitivity of our findings. Our results are robust to the choice of bandwidth selection criteria. See Section 4.1 for a detailed discussion.

¹⁴ This is a sufficiently large sample size for applying the semi-parametric panel data model estimated below. Our empirical model is a dynamic panel data model because it contains the lagged dependent variable as one of the explanatory variables. It is well known that the fixed effects model with a lagged dependent variable generates biased estimates when the time dimension (T) of the panel is small. Nickell (1981) derives an expression for this bias, showing that it approaches zero as T gets larger. Judson and Owen (1999) compare the performance of several different dynamic panel estimators in an extensive Monte Carlo study. Using a mean-squared-error criterion, they find that the fixed effects estimator performs just as well or better than many other alternatives when time dimension is 30. Because both of our sample periods contain 84 time series observations ($T = 84$), we utilize the fixed effects estimator throughout our empirical application.

¹⁵ Gonçalves and Kilian (2004) provide a detailed analysis of fixed- and recursive-design wild bootstrapping methods in autoregressive models. Su and Chen (2013) and Li et al. (2013) demonstrate fixed-design wild bootstrapping in parametric and nonparametric panel data models. Appendix B provides the details of our bootstrapping procedure.

Table 1
Parametric component of the semiparametric model.

Panel A: Jan 1995–Dec 2001		
	Coef	95% CI
$RPV_{i,t-1}$	0.746***	[0.668; 0.824]
Panel B: Jan 2004–Dec 2010		
	Coef	95% CI
$RPV_{i,t-1}$	0.734***	[0.668; 0.800]
$\pi_{i,t-1}$	0.072	[-0.108; 0.252]
$\pi_{i,t-2}$	-0.229***	[-0.320; -0.138]

Notes: This table displays the point estimates and 95% bootstrap confidence interval for the linear portion of the semiparametric model. Dependent variable is $RPV_{i,t}$. ***, **, * indicate significance at 1%, 5% and 10% levels, respectively.

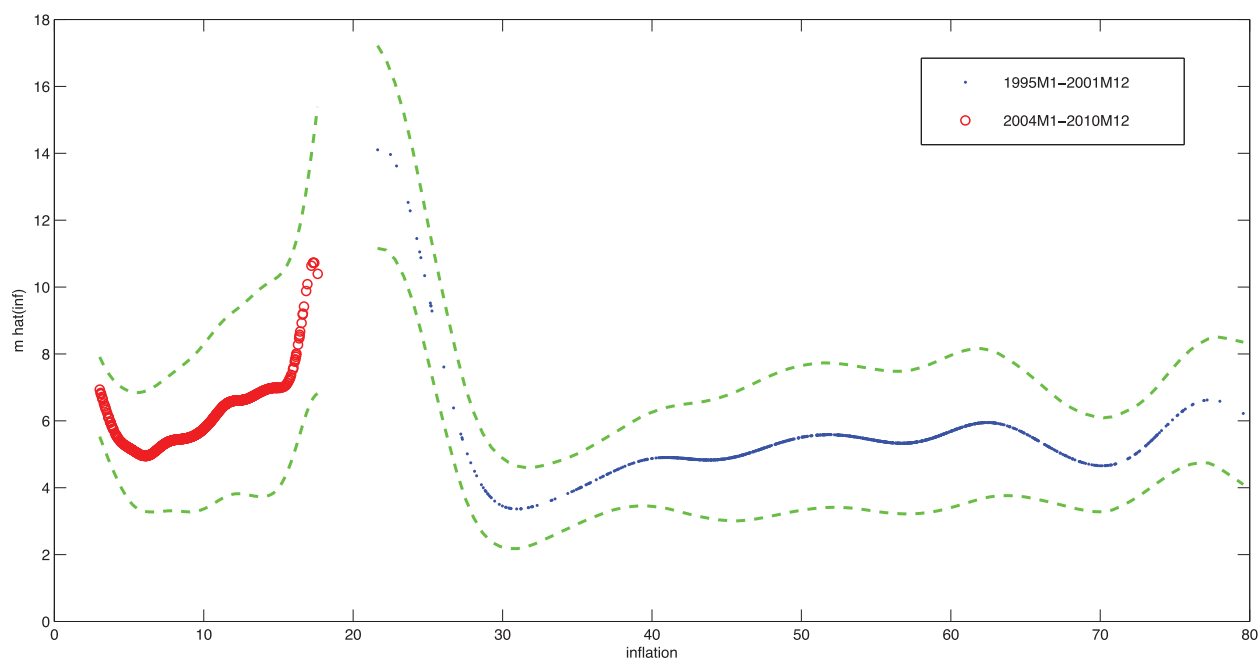


Fig. 2. Nonparametric Estimates of the inflation–RPV relationship Notes: The figure displays the nonparametric estimate of $m(\pi)$ for 1995:M1–2001:M12 (dots) and Jan 2004:M1–2010:M12 (circles). Dashed lines represent the 99% confidence interval for the nonparametric estimates.

1995:M1–2001:M12 and 2004:M1–2010:M12, respectively.¹⁶ From both panels, we observe that the estimates of $RPV_{i,t-1}$ are statistically significant and very similar in magnitude, 0.746 and 0.734, which implies a persistent behavior of current price variability.

As indicated above, our semi-parametric approach permits us to estimate the unknown inflation function, $m(\pi_{i,t})$, at all points of inflation in our samples. Fig. 2 illustrates the nonparametric estimate of $m(\pi_{i,t})$ along with the bootstrapped (99%) confidence intervals for both the initial and recent sample periods. Overall, the effect of inflation on RPV is hump-shaped. Although the effect decreases with very low inflation levels, i.e., when inflation is between 2% and 6%, it begins to increase when inflation reaches between 6% and 18%.¹⁷ The effect declines again when inflation is in the range of 22–30%. This second negative impact of inflation on RPV attains its minimum and disappears when inflation is approximately 30%. Then, as inflation increases, its effect on RPV becomes positive, although small in magnitude, as the slightly positively sloped $\hat{m}(\pi_{i,t})$ function indicates. As mentioned in the introduction above, in a recent study, Choi et al. (2011) suggested that the inflation–RPV nexus seems linear for high-inflation regimes but shows a nonlinear U-shape in more stable inflation environments.

¹⁶ Model selection, i.e., the choice of the number of lags for the linear part of our semi-parametric model, is accomplished based on the Akaike and Bayesian information criteria (see Claeskens and Hjort, 2008 for cross-validation of some well-known model selection criteria for the semi-parametric models). For the initial period of 1995:M1–2001:M12, both criteria indicated that only the first lag of RPV are appropriate to include in the model. However, for the recent period 2004:M1–2010:M12, they indicate that both the first lag of RPV and first two lags of inflation should enter into the linear component of the model. We do not report the results here to save space but they are available from the authors upon request.

¹⁷ There is discontinuity in the curve at approximately 18–22% inflation, as neither sample covers inflation in this range.

Overall, for a wide range of inflation levels, our study indicates a hump-shaped relation, which is a result consistent with this evidence. During the high-inflation episode, the relation approximates a linear form, while it is reminiscent of a U-shaped relation during the low-inflation period.¹⁸

3. Model

Having provided evidence of a hump-shaped relation between RPV and inflation, in this section, we show that this result is consistent with a region- or city-level homogenous menu cost model. This homogenous menu cost model features Calvo pricing with an endogenous contract structure and non-zero steady-state inflation. We obtain this disaggregated model by expanding the aggregate model of Levin and Yun (2007) into a multi-region framework. While the model of Levin and Yun (2007) focuses on relative price-level variability, our model analyzes the effect of inflation on relative price change (inflation) variability.

3.1. Implications of the model for RPV

To save space, the micro-foundations of the model are illustrated in Appendix C. In the following, we focus on the implications of the model for the relative price variability ϕ^r at the region or city level, which is given by the following steady-state expression:

$$\phi^r = \text{var}_g(\pi_g^r|r) = \frac{\theta^r(2 - \theta^r)(\pi^r)^2}{(1 - \theta^r + (\theta^r)^2)(1 - \theta^r)}, \tag{3}$$

where π_g^r is the steady-state inflation of good g in region/city r , $\text{var}_g(\pi_g^r|r)$ is the variance of π_g^r across goods (for any given r) that is consistent with RPV definition used in the empirical analysis above, π^r is the steady-state gross inflation for region/city r , and θ^r measures the endogenously determined price stickiness in region/city r determined according to the following discounted sum of profits, which is common across all firms in region/city r according to a symmetric Nash equilibrium:

$$\Omega_k^r = \frac{1 - \theta^r \beta}{1 - \beta} \left[\sum_{k=0}^{\infty} (\beta \theta^r)^k \left[\left(\frac{\tilde{p}^{r*}}{(\Pi^r)^k} \right)^{1-\varepsilon} - MC^r \left(\frac{\tilde{p}^{r*}}{(\Pi^r)^k} \right)^{-\varepsilon} \right] - \omega \right], \tag{4}$$

where β is the discount factor, $\Pi^r (= \exp \pi^r)$ is the gross inflation, ε is the elasticity of substitution across goods, ω is the share of menu cost in output for firms with non-zero constant menu cost, and \tilde{p}^{r*} is the relative price of profit maximizing price given by the following expression in the steady state:

$$\frac{\tilde{p}^{r*}}{P^r} = \frac{\bar{P}^r}{P^r} = \left(\frac{1 - \theta^r (\Pi^r)^{\varepsilon-1}}{(1 - \theta^r)} \right)^{\frac{1}{1-\varepsilon}},$$

where \bar{P}_t^r is the newly set price and P^r is the price index in region/city r ; MC^r is the marginal cost given by the following expression in the steady state:

$$MC^r = \left(\frac{\varepsilon - 1}{\varepsilon} \right) \left(\frac{1 - \theta^r \beta (\Pi^r)^{\varepsilon}}{1 - \theta^r \beta (\Pi^r)^{\varepsilon-1}} \right) \tilde{p}^{r*}. \tag{5}$$

3.2. Simulation of the model

To show the implications of the model for RPV, we must parameterize the discount factor β , elasticity of substitution ε , and share of the menu cost in output ω . Accordingly, we follow Levin and Yun (2007) to set $\beta = 0.984$ and $\omega = 0.029$; we also consider alternative values of ε ranging between 5 and 25 to test for robustness. As in Levin and Yun (2007), we assume that there are no endogenous fluctuations of real output, which implies that we search for a value of θ^r satisfying $\theta^r = \arg \max \Omega_k^r$, where Ω_k^r is given in Eq. (4).¹⁹

The implications of the model for the relation between the frequency of price change (i.e., $1 - \theta^r$) and the inflation rate are presented in Fig. 3. As is evident, firms change their prices more frequently as the level of inflation increases, independent of the value of ε considered. Using the obtained θ^r values, we obtain the implications of the model for the relation between RPV and inflation according to Eq. (3). The results given in Fig. 4 indicate that the model successfully replicated the hump-shaped relation between RPV and inflation, independent of the value of ε considered.

¹⁸ Choi et al. (2011) indicated that in high-inflation countries not adopting IT, including Turkey, a decrease in inflation has not led to a shift to U-shaped relationship from a linear one. However, this shift has occurred in IT countries with high inflation. Indeed, our results indicate that this shift may have occurred. Given that their data for the period 1986:M1–2009:M9 cover only 5 products without a regional dimension, it is possible that the shift cannot be captured by their data.

¹⁹ We set the number of periods to 100 while searching for $\theta^r = \arg \max \Omega_k^r$ in Eq. (4).

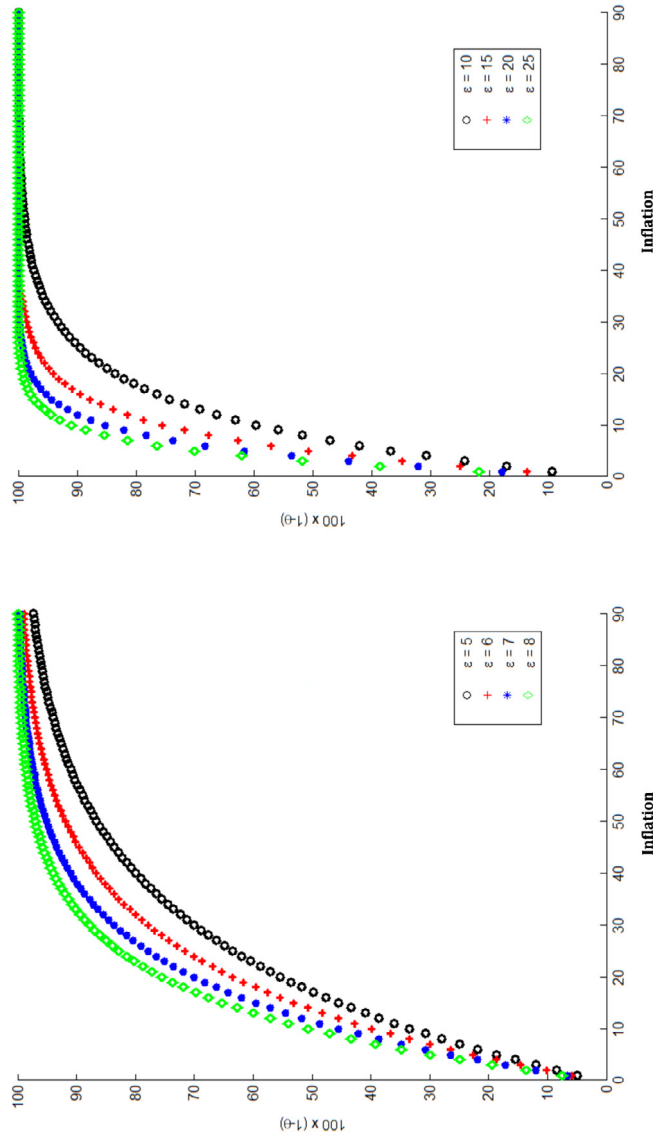


Fig. 3. The implication of the model: frequency of price change versus inflation. Notes: The vertical axis represents the percentage of firms changing their prices. ϵ represents the elasticity of substitution across goods.

In terms of the economic intuition, there are two opposite effects determining the hump-shaped relationship between RPV and inflation. One is the positive effect of inflation itself on RPV due to its scale because variance is a measure that increases with the level of the variable in consideration. This is the same effect that we observe in existing studies featuring *exogenous* Calvo parameters. The other is the negative effect of higher inflation on RPV through price stickiness that is determined by firm optimization (by considering the level of inflation), which is new in this paper. In particular, because firms choose their Calvo parameter (i.e., they decide their frequency of price change subject to a menu cost), they choose to change their prices when inflation increases (due to the opportunity cost of not changing their prices); hence, price stickiness decreases with higher inflation. When a firm changes its price, the new price reflects the changes in the nationwide inflation; therefore, when many firms change their prices, because inflation is a common measure across firms, the new prices become closer to each other and RPV decreases.

However, which of the two opposite effects is more effective in the determination of the inflation–RPV nexus depends on the elasticity of substitution, which is the key parameter showing the importance of inflation in firm optimization (see Eq. (4)). In particular, the effect of inflation on profit maximization increases with the elasticity of substitution, which is due to increasing competition across firms when their products become more substitutable. Hence, as the elasticity of substitution increases, more firms change their prices for a given level of inflation, which leads into a reduction in price stickiness. It is implied that the negative effect of higher inflation on RPV (due to price stickiness) becomes more effective compared

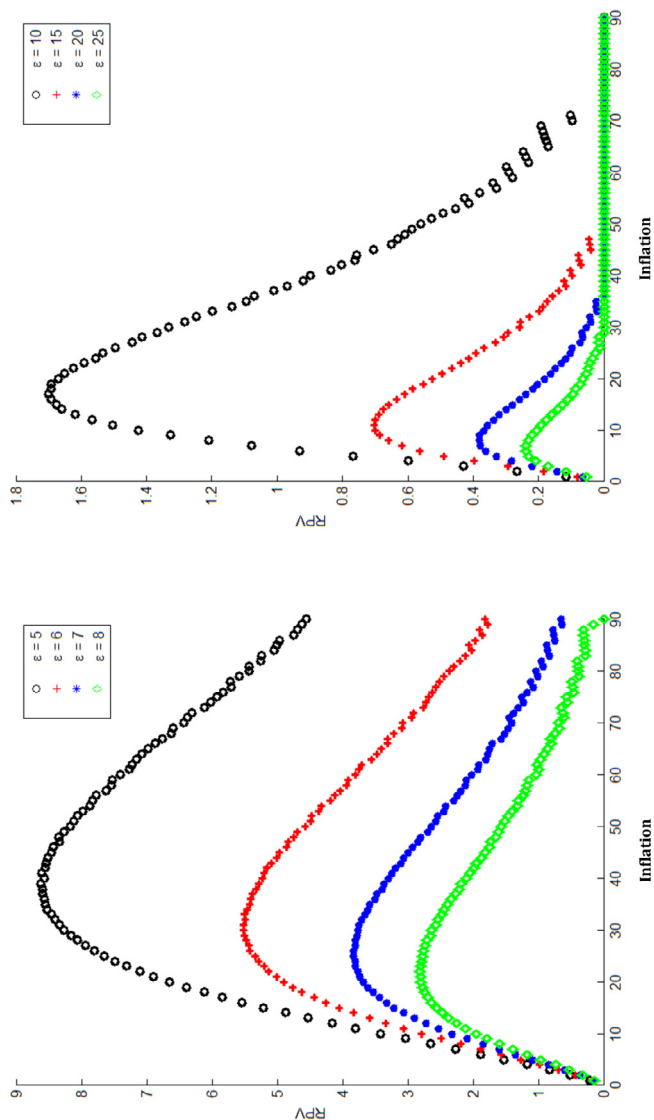


Fig. 4. The implication of the model: relative price variability versus inflation. Notes: The size of menu cost is set to be 2.9% of labor input (i.e., $\omega = 0.029$); because we assume that the production function is linear in labor, it means that the menu cost is 2.9% of the real output.

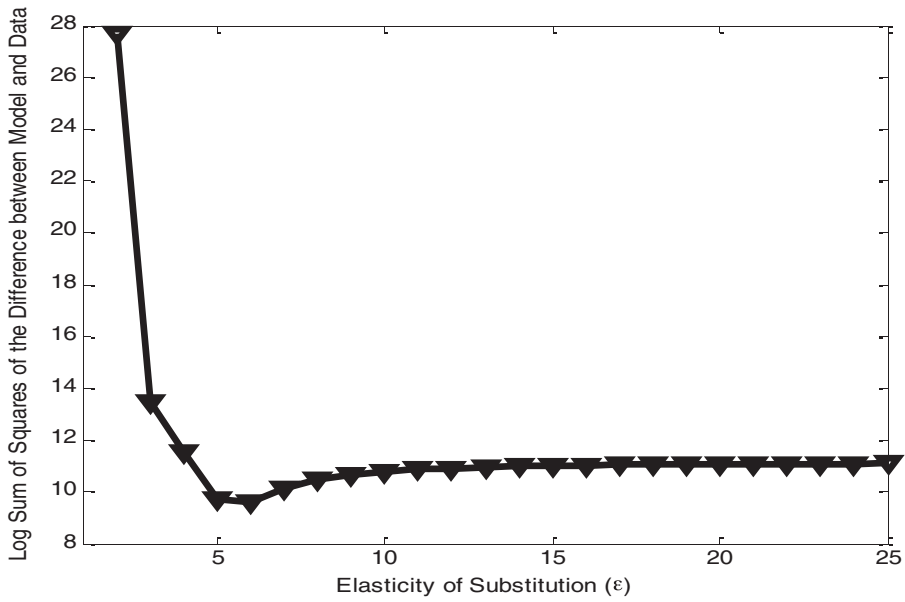
to the positive effect of higher inflation on RPV (due to the scale effect) as the elasticity of substitution increases; therefore, a hump-shaped relationship is implied for the inflation–RPV nexus.

Although we have shown that the model successfully replicates the data-oriented hump-shaped relationship between RPV and inflation for alternative values of the elasticity of substitution ε , we also would like to know the particular value of ε that maximizes the model fit, *ceteris paribus*. Accordingly, we consider a loss function based on the sum of squares of the difference between actual RPV data and RVP values implied by the model. As shown in Panel (a) of Fig. 5, the minimization of this loss function is achieved when $\varepsilon = 6$. Therefore, one can consider $\varepsilon = 6$ as the elasticity of substitution maximizing the model fit; this is also graphically shown by Panel b in Fig. 5. This value for the elasticity of substitution (i.e., $\varepsilon = 6$) is also consistent with existing studies such as that by Baier and Bergstrand (2001), whose estimate is approximately 6.4; Harrigan (1996)’s estimates ranging from 5 to 10; Feenstra (1994)’s estimates ranging from 3 to 8.4; Romalis (2007)’s estimates ranging from 6.2 to 10.9; and Broda and Weinstein (2006)’s estimates ranging from 4 to 17.3.

4. Robustness checks

This section conducts several robustness checks on the provided empirical results, including the consideration of alternative bandwidth choices in the semi-parametric analysis, anticipated versus unanticipated inflation, and business cycles.

(a) Elasticity of Substitution and Fit of the Model



(b) Inflation and RPV

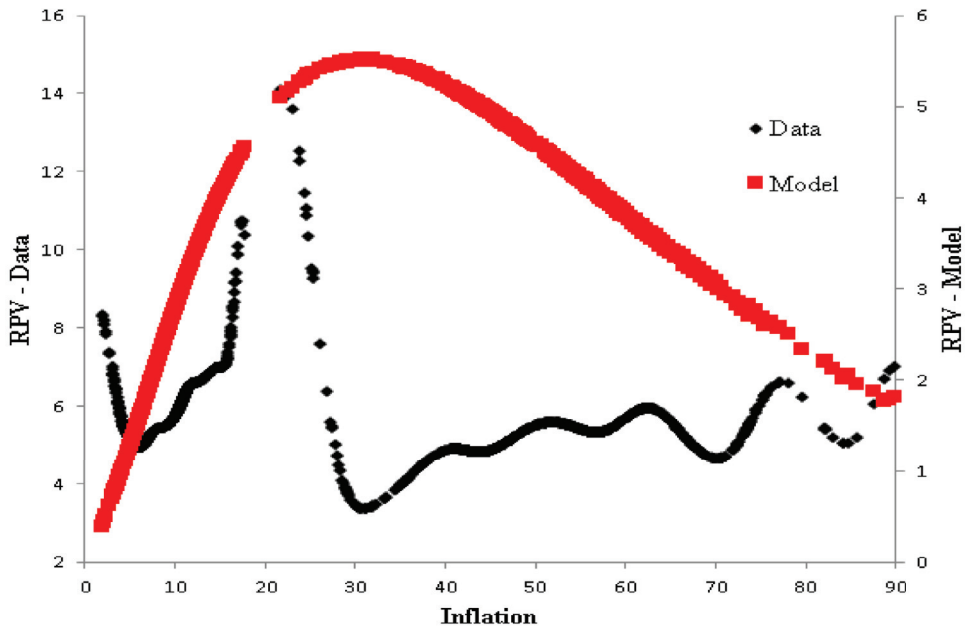


Fig. 5. Model versus data. Notes: Panel (a) shows the performance of the model (measured by the log sum of squares of the difference between the model and the actual data) for alternative measures of the elasticity of substitution. The best fit is achieved when the elasticity of substitution is equal to 6. Panel (b) shows the inflation–RPV nexus for the data and the model when the elasticity is substitution is equal to 6.

4.1. Bandwidth choice

Estimation of the smoothing parameter (bandwidth) is crucial in semi-parametric analysis. Selecting a very small bandwidth may produce an under-smoothed (low bias, high variance) estimator, while choosing a very large bandwidth may generate an over-smoothed (high bias, low variance) estimator. This is a well-known trade-off in applied nonparametric econometrics, and automated determination procedures are generally utilized to estimate the bandwidths. There exist many

Table 2
Bandwidths for the semiparametric regression.

	Jan 1995–Dec 2001	Jan 2004–Dec 2010
Rule of thumb	3.299	0.820
CV least-squares	1.768	1.180
CV AIC	1.873	1.521

Notes: This table reports the bandwidths obtained using the rule of thumb, least-squares cross-validation, and Kullback–Leibler criteria described in the text for the semiparametric regression.

selection procedures to estimate the optimal bandwidth in practice. Due to its computational simplicity and attractiveness to practitioners, we utilize the normal reference rule-of-thumb $h = 1.06s_z(NT)^{-1/5}$, where s_z is the sample standard deviation of $\{z_j\}_{j=1}^{NT}$. To check the sensitivity of our results, we also implemented two data-driven bandwidth selection techniques, least-squares cross-validation and [Hurvich et al. \(1998\)](#)'s Expected Kullback Leibler (AIC_c) criteria.

Least-squares cross-validation (LSCV) is one of the most popular techniques among the data-driven methods. For each observation in the data, this approach evaluates the error using kernel regression with that observation removed from the modeling process. The optimal bandwidth is then picked chosen to minimize the sum of squares of the errors from all of the observations. In particular, the bandwidth is chosen to minimize

$$CV(h) = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \{RPV_{i,t} - \hat{m}^{-i,t}(\pi_{i,t})\}^2$$

where $m^{-i,t}(\pi_{i,t})$ is the leave-one-out estimator of $m(\cdot)$.

Another attractive method is [Hurvich et al. \(1998\)](#)'s Expected Kullback Leibler criteria. This procedure selects the bandwidth using an improved version of a criterion based on the Akaike Information Criteria. Other methods, such as LSCV, have the weakness to undersmooth, but this problem is avoided by AIC_c . The bandwidth is selected to minimize

$$AIC_c = \log(\hat{\sigma}^2) + \frac{1 + \text{tr}(H)/NT}{1 - [\text{tr}(H) + 2]/NT}$$

where $\text{tr}(H)$ is the trace of H , H is the matrix of kernel weights, and

$$\hat{\sigma}^2 = \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T \{RPV_{i,t} - \hat{m}^{-i,t}(\pi_{i,t})\}^2$$

where $m^{-i,t}(\pi_{i,t})$ is the leave-one-out estimator of $m(\cdot)$.

[Table 2](#) displays the optimal bandwidths computed with the procedures discussed above. For our initial sample period 1995:M1–2001:M12, which is a high-inflation period, LSCV and AIC_c produce very similar bandwidths, and the bandwidth from the rule of thumb is larger in magnitude. [Fig. 6](#) illustrates the nonparametric estimate of $m(\cdot)$ for the smoothing parameters selected based on these three methods. It is clear from the figure that $\hat{m}(\cdot)$ is not sensitive to the choice of the bandwidth procedure. LSCV and AIC_c produce almost identical estimates, while the rule of thumb gives a slightly smoother function.

[Table 2](#) indicates that the rule of thumb provides the smallest estimate for the smoothing parameter for our second sample period 2004:M1–2010:M12, which corresponds to the low-inflation period. It is followed by LSCV and AIC_c . Although we detect the rule of thumb as the largest bandwidth in the initial sample, it is the smallest bandwidth in our second sample because the standard deviation of inflation is approximately four times smaller in the latter; hence, the rule of thumb yields a smaller estimate. [Fig. 6](#) also displays the estimated relationship between inflation and RPV for the low-inflation period. All bandwidths deliver a U-shaped estimate with a minimum of approximately 6%. As inflation passes 6%, the rule of thumb produces somewhat larger point estimates in magnitude than LSCV and AIC_c . This is known as bias-variance trade-off, and we expect the rule of thumb to give less biased point estimates with a relatively higher variance. Overall, by combining our findings from two inflationary periods, [Fig. 6](#) reveals that the hump-shaped relationship between inflation and RPV estimated for a wide range of inflation levels is robust to the choice of the smoothing parameter.

4.2. Anticipated and unanticipated inflation

Based on our earlier discussion on the effects of anticipated versus unanticipated components of inflation on RPV, this subsection considers an alternative estimation strategy by considering the nonlinear nature of inflation. We follow the same procedure as [Lach and Tsiddon \(1992\)](#) to decompose inflation into its anticipated and unanticipated components. In particular, anticipated inflation is the prediction (one-month-ahead) of inflation, which is computed by the regression of current

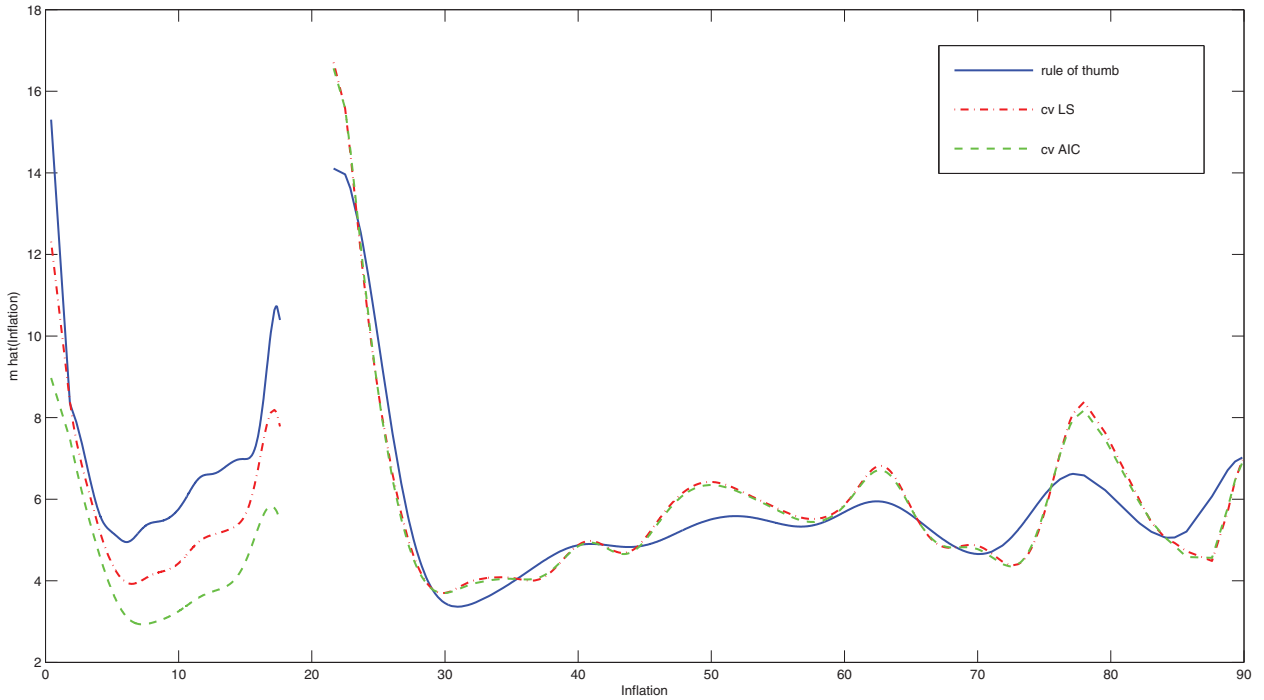


Fig. 6. Nonparametric estimates of $m(\pi)$ for various bandwidths. Notes: This figure illustrates the nonparametric estimate of $m(\pi)$ for the smoothing parameters selected based on rule of thumb (solid line), least-squares cross-validation (dashed-dotted line), and Kullback–Leibler criteria (dashed line) described in the text for the semi-parametric regression. The semi-parametric model assumes linearity for the lagged values of RPV and lagged values of inflation, and a smooth function for the inflation portion.

inflation on its previous lags, monthly time dummies, and city-specific fixed effects.²⁰ Unanticipated inflation is estimated as the residuals of these one-month predictions.

Using the identified components of inflation, we estimate the following model for the relationship between anticipated/unanticipated inflation and RPV:

$$RPV_{i,t} = \alpha_i + x'_{i,t}\gamma + m(\pi^A_{i,t}) + u_{i,t} \tag{6}$$

where $m(\cdot)$ is a smooth function; α_i 's represent city-specific fixed-effects; and x includes the lagged terms of RPV, the lagged terms of anticipated inflation (π^A), and both the current and lagged values of unanticipated inflation (π^U). Thus, the model allows analysis of the nonlinear relationship between anticipated inflation and RPV without imposing any specific functional form. Moreover, unanticipated inflation with other relevant explanatory variables are accounted for in a standard linear fashion.²¹ Table 3 displays the coefficient estimates and bootstrap confidence intervals for the variables that enter the model linearly. Panel A demonstrates our results for our initial sample, which is the high-inflation era. Both lagged RPV and unanticipated inflation have a positive and significant impact on RPV during the high-inflationary period. Panel B gives the linear component estimates from the low inflation era. We observe that lagged RPV has a positive and a significant effect on price variability, and this dynamic effect is very close in magnitude for both inflationary periods. While the current value of unanticipated inflation does not significantly affect RPV, its first and second lags have significant negative effects, with the first lag being more significant than the latter. Moreover, the first lag of anticipated inflation does not have any impact, whereas the second lag has a significant negative impact on RPV.

A nonlinear association between anticipated inflation and RPV is demonstrated in Fig. 7. Parallel to our earlier findings, we observe a U-shaped relationship when anticipated inflation is low, and the connection becomes flatter as anticipated inflation reaches a high-inflation episode. Therefore, the hump-shaped relationship survives even with the consideration of anticipated versus unanticipated components of inflation. Additionally, we find that unanticipated inflation increases the price variability in high-inflationary periods but does not alter it significantly in low-inflationary periods.

²⁰ The lag structure of inflation is selected according to the Bayesian Information criterion. The autoregressive order is estimated to be 13 for the period 1995:M1–2001:M12 and 6 for 2004:M1–2010:M12. We do not present our results for the sake of brevity. However, they are available from the authors upon request.

²¹ We employ the same number of lagged variables of RPV and inflation in our original model given by Eq. (2). Therefore, for 1995:M1–2001:M12, the first lag of RPV and current value of unanticipated inflation ($\pi^U_{i,t}$) enter the model linearly. For the recent period 2004:M1–2010:M12, both the first lag of RPV and first two lags of anticipated and unanticipated inflation along with the current value of unanticipated inflation ($\pi^A_{i,t-1}$, $\pi^A_{i,t-2}$, $\pi^U_{i,t}$, $\pi^U_{i,t-1}$, $\pi^U_{i,t-2}$) enter into the linear component of the model.

Table 3

Parametric component of the semiparametric model with anticipated and unanticipated inflation.

Panel A: Jan 1995–Dec 2001		
	Coef	95% CI
$RPV_{i,t-1}$	0.750***	[0.673; 0.826]
$\pi_{i,t}^u$	0.127***	[0.020; 0.235]
Panel B: Jan 2004–Dec 2010		
	Coef	95% CI
$RPV_{i,t-1}$	0.765***	[0.699; 0.832]
$\pi_{i,t-1}^A$	0.042	[-0.200; 0.284]
$\pi_{i,t-2}^A$	-0.333***	[-0.453; -0.212]
$\pi_{i,t}^U$	0.090	[-0.150; 0.330]
$\pi_{i,t-1}^U$	-0.257***	[-0.493; -0.021]
$\pi_{i,t-2}^U$	-0.176*	[-0.387; 0.036]

Notes: This table displays the point estimates and 95% bootstrap confidence interval for the linear portion of the semiparametric model when business cycle effects are captured with a recession dummy. The dependent variable is $RPV_{i,t}$. *Recession* is a dummy variable that takes a value of 1 during recessions and zero otherwise. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

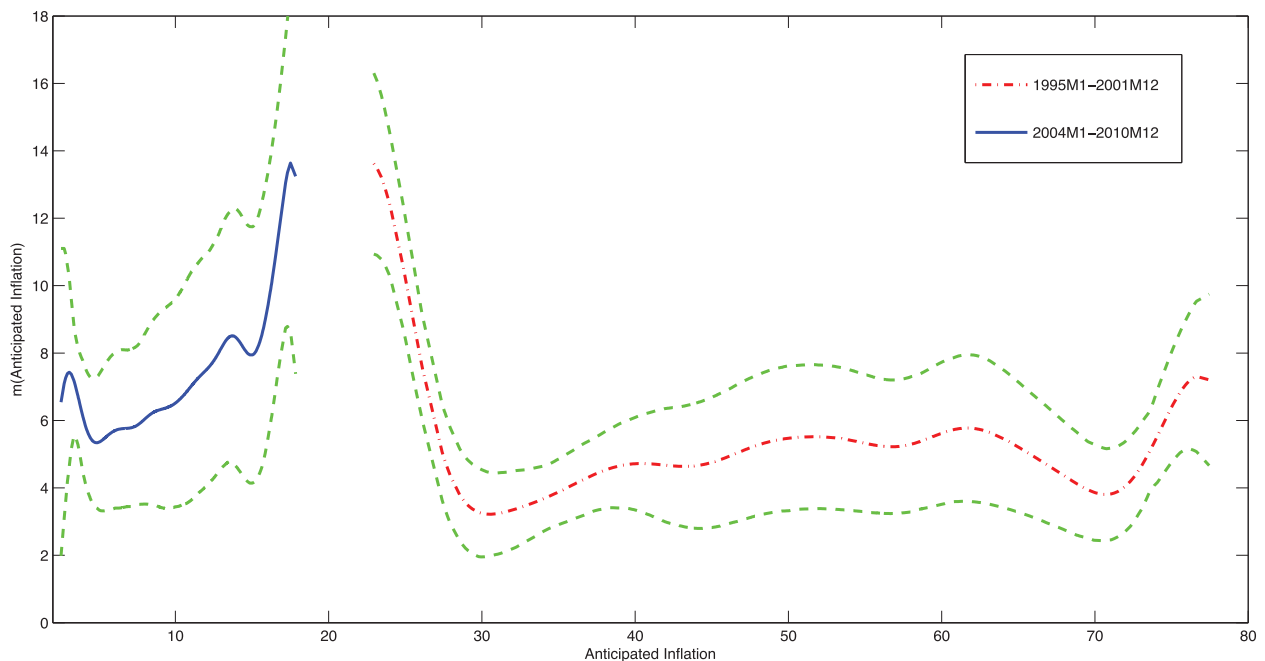


Fig. 7. Nonparametric estimates of the anticipated inflation–RPV relationship. Notes: This figure illustrates the nonparametric estimate of anticipated inflation, $m(\pi^A)$, and the corresponding 99% confidence interval. A solid line represents the point estimates for the period 1995:M1–2001:M12, and a dashed-dotted line represents the estimates for the period 2004:M1–2010:M12. Confidence bands are given in dashed lines. The semi-parametric model assumes linearity for the lagged values of RPV and lagged values of anticipated and unanticipated inflation and a smooth function for the anticipated inflation portion.

4.3. Business cycle effects

Our data set covers observations from 13 Turkish cities over 84 months for two inflationary (low-high) periods. It is possible that over the course of seven years, the relationship between relative price variability and inflation is affected by business cycle fluctuations. Excluding these fluctuations from our analysis may lead to biased estimates of the inflation–RPV relationship. The goal of this subsection is to verify whether the results presented in Section 2.2 are robust to capturing business cycles effects on the relationship.²²

²² We thank an anonymous referee for suggesting this analysis.

Table 4
Parametric component of the semiparametric model with recession effect.

Panel A: Jan 1995–Dec 2001		
	Coef	95% CI
$RPV_{i,t-1}$	0.747***	[0.665; 0.829]
$Recession_{i,t}$	0.047	[-0.377; 0.471]
Panel B: Jan 2004–Dec 2010		
	Coef	95% CI
$RPV_{i,t-1}$	0.734***	[0.669; 0.800]
$Inf_{i,t-1}$	0.073	[-0.108; 0.253]
$Inf_{i,t-2}$	-0.207***	[-0.298; -0.117]
$Recession_{i,t}$	-0.395**	[-0.729; -0.061]

Notes: This table displays the point estimates and 95% bootstrap confidence interval for the linear portion of the semiparametric model. The dependent variable is $RPV_{i,t}$; $Recession^{1998}$, $Recession^{2000}$, $Recession^{2006}$ are dummy variables for the recessions between Jan 1998 and July 1999, Aug 2000 and Sep 2001, July 2006 and Feb 2009, respectively. ***, **, * indicate significance at the 1%, 5% and 10% levels, respectively.

One possible way of incorporating the effect of economic cycles in our empirical model is to use a dummy variable, which takes the value one through recessions and zero otherwise. While our initial sample covers two recessions, 1998:M1–1999:M7 and 2000:M8–2001:M9, our second sample contains only one recessionary episode, 2006:M7–2009:M2. Therefore, 38% of the observations in each sample correspond to recessionary periods; whereas 33 months suffer from recessions in our initial sample, 32 months experience recessions in the second sample.²³ Accordingly, we estimate the following regression:

$$RPV_{i,t} = \alpha_i + x'_{i,t}\gamma + \beta Recession_t + m(\pi_{i,t}) + u_{i,t} \quad (7)$$

where $Recession$ is the recession dummy, and all other variables are identical with our model in Eq. (2). Table 4 displays the point estimates and the confidence interval for the parametric portion of the model. As is evident, our estimates are parallel to our findings from Table 1. In particular, the current value of RPV has a persistent nature in both sample periods; the first lag of inflation has a positive but insignificant effect, and the second lag of inflation has a significant negative effect on RPV in the second period. The impact of recessions on price variability is quite different for the two episodes of inflation: while the effects of a recession are not significant in the high-inflationary era, they are negative and significant during the low-inflationary period. This result is consistent with studies such as that by Vavra (2014), who shows that the frequency of price change is countercyclical in the U.S. CPI data that cover low-inflationary episodes. In particular, recessionary periods correspond to a higher frequency of price changes, which, in turn, reduce relative price variability when inflation is low, while the frequency of price change is already high during high-inflationary episodes (according to our model), as depicted in Fig. 3. Fig. 8 exhibits the resulting nonparametric estimates of inflation when business cycle effects are accounted for. It is clear that the effect of inflation on RPV is hump-shaped. Moreover, we observe vastly similar nonparametric estimates of inflation for Figs. 8 and 2.

As a final robustness check, instead of using one dummy variable to pick up the influence of business cycles, we utilize a dummy variable for each recession in our data set. Table 5 and Fig. 9 demonstrate our semi-parametric estimates, which are highly analogous to our results shown in Table 4 and Fig. 8. As is evident, the hump-shaped relationship between inflation and RPV does not vanish when business cycle fluctuations are incorporated into our semi-parametric panel data model.

5. Conclusions

In this paper, we present empirical evidence of a hump-shaped relation between RPV and inflation that is shown to be consistent with a homogenous menu cost model featuring Calvo pricing, an endogenous contract structure, and non-zero steady-state inflation. This evidence indicates that the inflation–RPV nexus exhibits quite different dynamics depending on the inflationary environment, consistent with Choi et al. (2011), where the inflation–RPV relation is found to be linear in high-inflation regimes but nonlinear and U-shaped in more stable environments. Although this hump-shaped relation seems inconsistent with the U-shaped relation found in the empirical literature (e.g., Choi, 2010; Choi and Kim, 2010; Fielding and Mizen, 2008), because this study covers periods with much higher levels of inflation (ranging between 0% and 90%), this result may be considered a generalization of the results in earlier studies, suggesting that the U-shaped relation can be confined to periods with relatively low levels of inflation but not long-lasting high inflation.

The hump-shaped relation between RPV and inflation is also shown to be robust to the consideration of alternative empirical strategies; these include (i) alternative smoothing parameters that are crucial in semi-parametric analysis, (ii) the

²³ Recession indicators for Turkey are taken from the FRED database at <https://research.stlouisfed.org/fred2/series/TURRECM>.

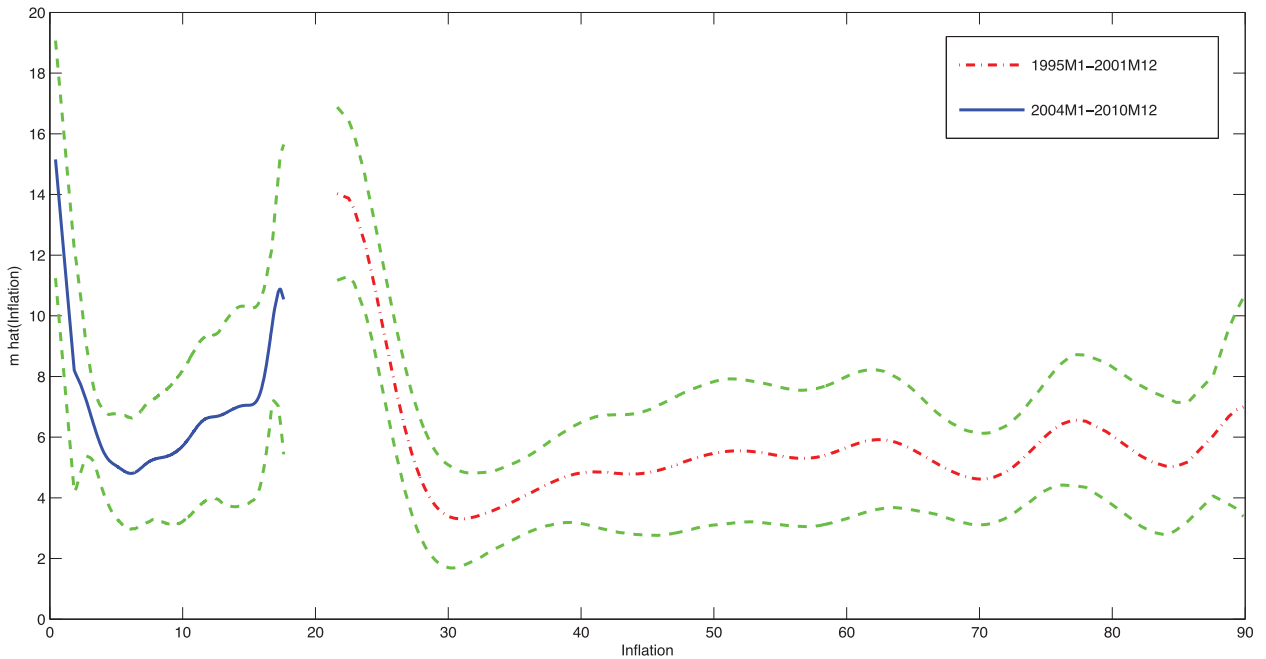


Fig. 8. Nonparametric estimates of the inflation–RPV relationship controlling for recession effect. Notes: This figure illustrates the nonparametric estimate of inflation, $m(\pi)$, and the corresponding 99% confidence interval when business cycle effects are controlled with a recession dummy. A solid line represents the point estimates for the period 1995:M1–2001:M12, and a dashed-dotted line represents the estimates for the period 2004:M1–2010:M12. Confidence bands are given in dashed lines. The semi-parametric model assumes linearity for the lagged values of RPV, lagged values of inflation and the recession dummy, and a smooth function for the inflation portion.

Table 5

Parametric component of the semiparametric model controlling for each recession.

Panel A: Jan 1995–Dec 2001		
	Coef	95% CI
$RPV_{i,t-1}$	0.747***	[0.665; 0.828]
$Recession^{1998}$	−0.121	[−0.581; 0.339]
$Recession^{2000}$	0.572**	[0.083; 1.061]
Panel B: Jan 2004–Dec 2010		
	Coef	95% CI
$RPV_{i,t-1}$	0.734***	[0.669; 0.800]
$lnf_{i,t-1}$	0.073	[−0.108; 0.253]
$lnf_{i,t-2}$	−0.207***	[−0.298; −0.117]
$Recession^{2006}$	−0.395**	[−0.729; −0.061]

Notes: This table displays the point estimates and 95% bootstrap confidence interval for the linear portion of the semiparametric model. Dependent variable is $RPV_{i,t}$; $Recession^{1998}$, $Recession^{2000}$, $Recession^{2006}$ are dummy variables for the recessions between Jan 1998 and July 1999, Aug 2000 and Sep 2001, July 2006 and Feb 2009, respectively. ***, **, * indicate significance at 1%, 5% and 10% level, respectively.

distinction between anticipated versus unanticipated inflation regarding their effects on RPV, and (iii) the consideration of business cycles that may affect the inflation–RPV nexus. However, the results are not without caveats. For instance, we have not considered the role of the level of aggregation in our price data (as is standard in studies focusing on subindices of CPI) because we already have the most disaggregated level micro-price data; therefore, the comparison of our results with the existing studies should be achieved by considering this difference. Moreover, non-zero steady-state inflation (as we have considered in this paper) may not be the only reason behind the mixed evidence in the existing literature (as summarized in Appendix Table A1), although it has been effective in explaining the inflation–RPV nexus for a sample covering a wide range of inflation. Accordingly, future research can explore systematic explanations other than non-zero steady-state inflation; such an investigation can be achieved by using a meta-data analysis, which seems to be necessary.

Table A1
Summary of empirical studies on inflation–RPV nexus.

Paper by	Data	Methodology	Finding
Parks (1978)	The expenditure and implicit deflator series of 12-commodity breakdown annually for the years 1929–1975 in the U.S.	Simple time series regressions	RPV increases more (less) during periods of price decreases (increases)
Tommasi (1992)	Weekly prices of 15 products in 5 supermarkets within the same neighborhood in the Federal District of Buenos Aires for 46 weeks from February to December 1990	Time series analysis	Symmetric V-shaped relationship between inflation and RPV
Reinsdorf (1994)	U.S. monthly consumer price index data for nine cities covering 65 food categories for the Volcker disinflation period of 1980–1982	Cross sectional regressions for each year and for each city	There is a negative relationship between inflation and price dispersion. Declines in price dispersion follow unexpected inflation, while expected inflation has a positive impact on price dispersion
Debelle and Lamont (1996)	Two balanced panels of annual Consumer Price Index inflation rates for US cities. The first panel runs from 1954 to 1986 for 19 US cities and 14 categories of goods and services. The second panel runs from 1977 to 1986 and includes 5 additional cities, and 4 additional categories	Cross-sectional and panel regressions	Symmetric V-shaped relationship between inflation and RPV. Cities with higher than average inflation also have higher than average relative price dispersion
Carballo et al. (2006)	Monthly wholesale price index for Argentina (covering the period from 1960 to 2001) and monthly consumer price index for Spain (covering the period from 1985 to 2001)	Time series regressions	A non-concave relationship between RPV and inflation in Argentina, denoting that inflation affects RPV more than proportionally beyond a certain threshold of inflation
Jaramillo (1999)	Personal consumption expenditures and producer price index annual data covering the period between 1948 and 1996	Time series regressions	Both positive and negative rates of inflation have positive and significant effects on price dispersion, although the effects differ in magnitude
Fielding and Mizen (2000)	Monthly commodity-level price data covering 15 product groups from 10 EU countries between 1986 and 1993	Time series regressions	Evidence for a significant negative relationship between RVP and inflation within product groups
Silver and Ioannidis (2001)	Monthly consumer price index data covering 19 product groups from 9 European countries between 1981 and 1989	Seemingly unrelated regressions at the country level	Unexpected inflation has a negative effect on RPV for all countries, while expected inflation has a negative effect on RPV for most countries
Caglayan and Filiztekin (2003)	Annual price data for 22 food products from 19 Turkish cities covering the period between 1948 and 1997	Panel data estimations	Nonlinear relationship between price variability and inflation for both expected and unexpected inflation
Fielding and Mizen (2008)	Quarterly personal consumer expenditure data in the U.S. covering the period between 1967 and 2003	Semi-parametric time series and non-parametric regressions	The empirical RPV function yields a plausible 'optimal' value of inflation in the region of 5%
Bick and Nautz (2008)	Monthly consumer price indices for 8 categories covering 14 U.S. cities between 1998 and 2005	Modified version of Hansen's panel threshold model	Inflation decreases (increases) RPV below 1.67% (if it exceeds a range from about 2.8% to 4.4%).
Choi (2010)	Monthly consumer price indices for 38 and 47 product categories covering the periods between 1978–2007 and 1970–2006 from the U.S. and Japan, respectively	Time series, semi-parametric, rolling regressions with multivariate multiple structural break tests	U-shaped relationship between inflation and RPV for low inflation rates; U-shaped relationship vanishes for high inflation rates
Choi and Kim (2010)	Monthly consumer price indices for 36, 47 and 38 good categories covering the periods between 1984–2005, 1984–2006 and 1984–2007 from Canada, Japan, and the U.S., respectively	Time series regressions and piecewise linear models	A relationship between inflation and RPV depends on the deviation of inflation from its target level perceived by the public
Becker (2011)	Monthly sectoral price data covering 12 Euro countries over the period between 1996 and 2008	Panel data regression	U-shaped (flatter) relationship between inflation and RPV in markets with high (low) markups
Choi et al. (2011)	Monthly and quarterly consumer price indices at the subcategory level for 12 inflation-targeting countries covering the period between 1984 and 2009	Time series and semi-parametric regressions	U-shaped relationship between inflation and RPV, where the minimum RPV is close to the announced inflation target
Nautz and Scharff (2012)	Monthly consumer price indices covering 12 subcategories for 13 Euro countries for the period between 1999 and 2006	Panel data and panel threshold regressions	U-shaped relationship between inflation and RPV. Expected inflation significantly increases RPV only if annual inflation rate is below 0.95% or above 4.96%

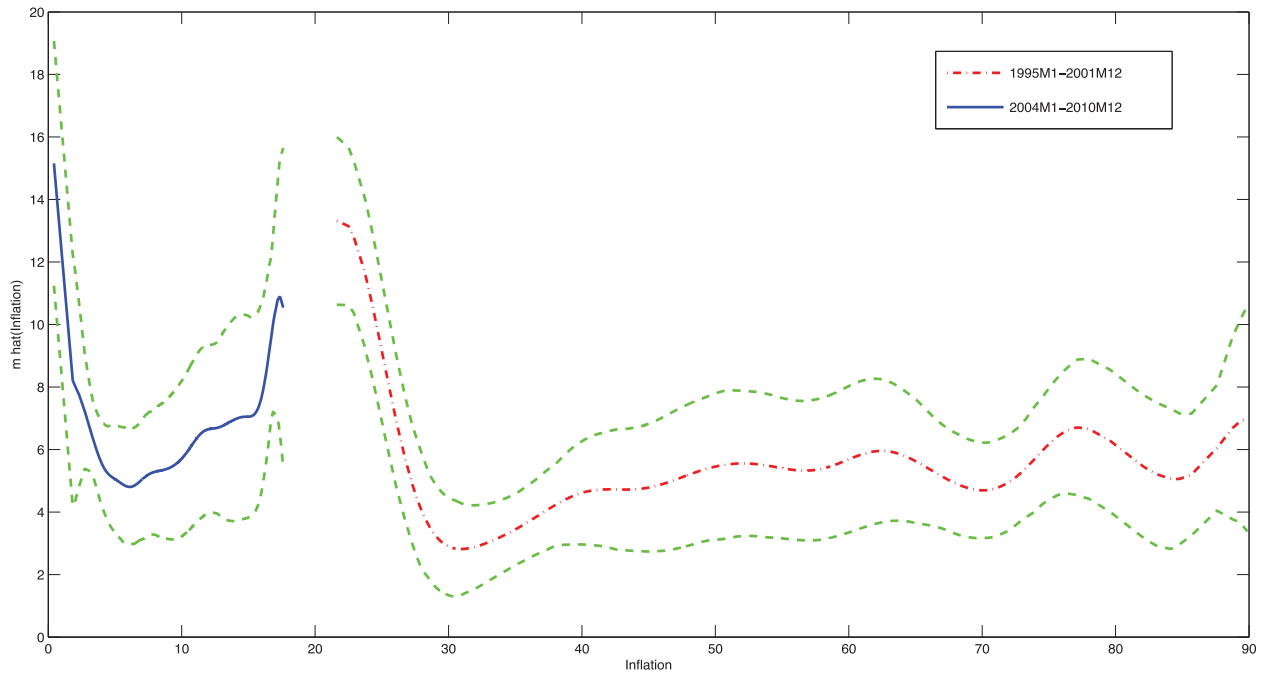


Fig. 9. Nonparametric estimates of the inflation–RPV relationship controlling for each recession. Notes: This figure illustrates the nonparametric estimate of inflation, $m(\pi)$, and the corresponding 99% confidence interval when business cycle effects are controlled with a dummy for each recession. A solid line represents the point estimates for the period 1995:M1–2001:M12, and a dashed-dotted line represents the estimates for the period 2004:M1–2010:M12. Confidence bands are given in dashed lines. The semi-parametric model assumes linearity for the lagged values of RPV, lagged values of inflation and the recession dummies, and a smooth function for the inflation portion.

Appendix A. Data

We use seasonally adjusted good-level prices for cities and regions in Turkey that were obtained from the Turkish Statistical Institute (TurkStat). The monthly prices are reported at the retail level. The total number of retail stores throughout Turkey is 22,886, but the number of stores varies by region.²⁴ The prices for each good in each region were averaged across retail stores to calculate region-specific good prices; these raw retail prices are used to calculate the consumer price index in Turkey.²⁵

A change in the collection of price data in 2003 created two sample periods. The first covers monthly periods between 1994:M1 and 2001:M12 and includes 554 good prices from 23 regions in Turkey. The second covers monthly periods between 2003:M1 and 2010:M12 and includes 449 good prices from 26 regions in Turkey. Because our main objective is to create a single data set covering both periods, we focus on the common set of cities/regions and goods, which includes the prices of 128 goods and 13 cities/regions. This is the same data set used by Yazgan and Yilmazkuday (2016) to compare the convergence properties of price levels across high- and low-inflation periods.

Appendix B. Econometric methodology

The semi-parametric panel data model of interest is given by

$$y_{it} = \alpha_i + x'_{it}\gamma + m(z_{it}) + u_{it}, \quad i = 1, \dots, N, \quad t = 1, \dots, T, \quad (\text{B.1})$$

where α_i 's are fixed effects, x_{it} is a p -dimensional vector of regressors, $m(\cdot)$ is a smooth function, z_{it} is a q -dimensional vector of exogenous regressors, and u_{it} are zero mean *i.i.d* innovations with variance σ_u^2 . Therefore, we include heterogeneity through individual fixed effects and analyze the nonlinear relationship of interest without imposing a specific functional form, controlling other important explanatory variables. For identification, we assume $\sum_{i=1}^N \alpha_i = 0$.

Taking a first order Taylor expansion of (B.1) at point z yields

$$y_{it} \approx \alpha_i + x'_{it}\gamma + m(z) + (z_{it} - z)\beta(z) + u_{it}$$

²⁴ These stores do not change over time unless a store closes or a particular product is no longer available in that store.

²⁵ The link between the good-level price data utilized in this paper and aggregate CPI data is achieved through good- and region-specific weights assigned to the individual prices.

$$= \alpha_i + x'_{it}\gamma + Z_{it}(z)\delta(z) + u_{it},$$

where $Z_{it}(z) = (1 \ (z_{it} - z)')'$, $\beta(z) = \frac{\partial m(z)}{\partial z}$, and $\delta(z) = (m(z) \ \beta(z)')$. In vector form, we have

$$Y \approx D\alpha + X\gamma + Z(z)\delta(z) + U, \tag{B.2}$$

where $Y = (y_{11}, \dots, y_{1T}, \dots, y_{n1}, \dots, y_{nT})'$, and $Z(z) = (Z_{11}(z), \dots, Z_{1T}(z), \dots, Z_{n1}(z), \dots, Z_{nT}(z))'$, $\alpha = (\alpha_2, \dots, \alpha_n)'$, $D = (I_n \otimes I_T) d_n$, $d_n = [-l_{n-1} I_{n-1}]'$, and l_a is an $a \times 1$ vector of ones.

Su and Ullah (2006) propose estimating the model in (B.2) using the profile least squares method. Their approach assumes that the individual effects parameter α and linear component γ are initially known and thus estimate $\delta(z)$ by minimizing the following criterion function:

$$(Y - D\alpha - X\gamma - Z(z)\delta)'K_h(z)(Y - D\alpha - X\gamma - Z(z)\delta),$$

where $K_h(z) = h^{-q}K(z/h)$, K is a kernel function and h is a bandwidth parameter. This procedure profiles out the model parameters and considers the concentrated least squares for $\delta(z)$. Defining the smoothing operator as $S(z) = [Z(z)'K_h(z)Z(z)]^{-1}Z(z)'K_h(z)$ and letting $\theta = (\alpha', \gamma)'$,

$$\delta_\theta(z) = S(z)(Y - D\alpha - X\gamma).$$

In particular, the estimator for $m(z)$ is

$$m_\theta(z) = s(z)'(Y - D\alpha - X\gamma),$$

where $s(z)' = e'S(z)$, and $e = (1, 0, \dots, 0)'$ is a $(q + 1) \times 1$ vector. However, $\delta_\theta(z)$ depends on the unknown parameter vector θ and hence is not operational. To operationalize $\delta_\theta(z)$, linear parameter γ and the fixed effects are estimated with the profile least squares method as follows:

$$\begin{aligned} \hat{\gamma} &= [X^*M^*X^*]^{-1}X^*M^*Y^*, \\ \hat{\alpha} &\equiv (\hat{\alpha}_2, \dots, \hat{\alpha}_n) = [D^*D^*]^{-1}D^*(Y - X^*\hat{\gamma}), \end{aligned}$$

where $D^* = (I_{nT} - S)D$, $Y^* = (I_{nT} - S)Y$, $X^* = (I_{nT} - S)X$, $M^* = I_{nT} - D^*[D^*D^*]^{-1}D^*$, $S = (s_{11}, \dots, s_{1T}, s_{21}, \dots, s_{nT})$, and $s_{it} = s(z_{it})$. Finally, the profile likelihood estimator for $\delta(z)$ is given by

$$\hat{\delta}(z) = \begin{bmatrix} \hat{m}(z) \\ \hat{\beta}(z) \end{bmatrix} = S(z)(Y - D\hat{\alpha} - X\hat{\gamma}).$$

Bootstrap

Following Su and Chen (2013) and Li et al. (2013), we implement a fixed-design wild bootstrapping procedure. The bootstrap confidence intervals are obtained via the following steps:

1. For each $i = 1, \dots, N$ and $t = 1, \dots, T$, obtain the bootstrap error $u_{it}^* = \hat{u}_{it}\varepsilon_{it}$, where $\hat{u}_{it} = y_{it} - \hat{y}_{it}$ and ε_{it} are *i.i.d* $N(0, 1)$ across i and t , and \hat{y}_{it} is the fitted value of y_{it} obtained from Eq. (B.1).
2. Generate the bootstrap sample $y_{it}^* = \hat{y}_{it} + u_{it}^*$ for $i = 1, \dots, N$ and $t = 1, \dots, T$.
3. Given a bootstrap sample for the dependent variable $\{(y_{it}^*, z_{it}, x_{it}), i = 1, \dots, N, t = 1, \dots, T\}$ obtain the estimators of $m(\cdot)$ and γ and denote the resulting estimates by $\hat{m}^*(\cdot)$ and $\hat{\gamma}^*$.
4. Repeat steps (1)–(3) a large number (B) of times to obtain the bootstrap samples $\hat{m}_b^*(\cdot)$ and $\hat{\gamma}_b^*$, $b = 1, \dots, B$. The estimators $Var^*(\hat{m}(\cdot))$ and $Var^*(\hat{\gamma})$ are the sample variances of $\hat{m}_b^*(\cdot)$ and $\hat{\gamma}_b^*$, respectively.
5. Compute $T_{m,b}^* = \frac{|\hat{m}_b^*(z) - \hat{m}(z)|}{\{Var^*(\hat{m}(z))\}^{1/2}}$ and $T_{\gamma,b}^* = \frac{|\hat{\gamma}_b^* - \hat{\gamma}|}{\{Var^*(\hat{\gamma})\}^{1/2}}$ for $b = 1, \dots, B$.
6. Use the upper α percentile of $T_{m,b}^*$ and $T_{\gamma,b}^*$, to estimate $c_{m,\alpha}$ and $c_{\gamma,\alpha}$.
7. Construct the $(1 - \alpha) \times 100\%$ bootstrapped confidence intervals as follows:

$$\begin{aligned} &\hat{m}(z) \pm \{Var(\hat{m}^*(z))\}^{1/2}c_{m,\alpha} \\ &\hat{\gamma} \pm \{Var(\hat{\gamma}^*)\}^{1/2}c_{\gamma,\alpha} \end{aligned}$$

Appendix C. Microfoundations of the model

The representative individual in region/city r is assumed to maximize her utility:

$$U_t^r = E_0 \sum_{t=0}^{\infty} \beta^t \left(\frac{(C_t^r)^{1-\sigma} - 1}{1-\sigma} - \frac{(N_t^r)^{1+\kappa}}{1+\kappa} \right), \tag{C.1}$$

where β is the discount factor, N_t^r is the number of hours worked, and C_t^r is an index of composite goods given by:

$$C_t^r = \left(\int_0^1 (c_{g,t}^r)^{\frac{\varepsilon-1}{\varepsilon}} dg \right)^{\frac{\varepsilon}{\varepsilon-1}},$$

where $C_{g,t}^r$ is the consumption of good g and $\varepsilon > 1$ is the elasticity of substitution across goods. The optimization results in the following demand functions:

$$C_{g,t}^r = \left(\frac{P_{g,t}^r}{P_t^r} \right)^{-\varepsilon} C_t^r,$$

where P_t^r and $P_{g,t}^r$ are the prices corresponding to C_t^r and $C_{g,t}^r$, respectively, which satisfy

$$P_t^r = \left(\int_0^1 (P_{g,t}^r)^{1-\varepsilon} dg \right)^{\frac{1}{1-\varepsilon}}. \tag{C.2}$$

The individual in region/city r chooses consumption C_t^r and labor supply N_t^r according to Eq. (C.1) with respect to the following budget constraint:

$$C_t^r + E_t \left(Q_{t,t+1} \frac{B_{t+1}^r}{P_{t+1}^r} \right) = \frac{B_t^r}{P_t^r} + \frac{W_t^r N_t^r}{P_t^r} + T_t^r,$$

where $Q_{t,t+1}$ is the stochastic discount factor for computing the real value at period t of one unit of consumption of goods in period $t + 1$, B_t^r is the nominal bonds portfolio, and T_t^r represents transfers/dividends. The optimization results in

$$Q_{t,t+1} = \beta \left(\frac{C_{t+1}^r}{C_t^r} \right)^{-\sigma} \left(\frac{P_t^r}{P_{t+1}^r} \right).$$

The firm producing good g in region r has the following market clearing condition:

$$Y_{g,t}^r = C_{g,t}^r,$$

where $Y_{g,t}^r$ is output. For the optimization problem of the firm, following Levin and Yun (2007), we consider deterministic steady states with constant real quantities over time and a symmetric Nash equilibrium with individual firms choosing the same frequency of price adjustments; this serves our purposes of analyzing the steady-state relationship between inflation and price dispersion across regions. We also assume that there are fixed costs associated with changing prices that are proportional to the output produced: $F_{g,t}^r = \omega Y_{g,t}^r$. In formal terms, a recursive representation of the present value of current and future profits for firms re-optimizing their prices at period $t - k$ is given by

$$\begin{aligned} \Omega_{g,k}^r(\theta_g^r, \theta^r) &= \underbrace{\left(\left(\frac{\tilde{P}_g^*}{(\Pi^r)^k} \right)^{1-\varepsilon} - MC^r \left(\frac{\tilde{P}_g^*}{(\Pi^r)^k} \right)^{-\varepsilon} \right) Y_g^r - I_{\{k=0\}} \omega Y_g^r}_{\text{One-Period Profit}} \\ &\quad + \underbrace{\beta \{ \theta_g^r \Omega_{g,k+1}^r(\theta_g^r, \theta^r) + (1 - \theta_g^r) \Omega_{g,0}^r(\theta_g^r, \theta^r) \}}_{\text{Recursive Term}}, \end{aligned}$$

where θ_g^r is the measure of price stickiness (θ^r is the mean measure across firms in region/city r), $\tilde{P}_g^* = \frac{P_{g,t}^r}{P_t^r}$ is the relative price of the profit maximizing price (where $\overline{P}_{g,t}^r$ is the newly set price), MC^r represents the marginal cost of production, and $I_{\{k=0\}} = 1$ only if $k = 0$. The firm chooses both θ_g^r and \overline{P}_g^r . First, \tilde{P}_g^* is determined by the following first-order condition:

$$\tilde{P}_g^* = \left(\frac{\varepsilon}{\varepsilon - 1} \right) \left(\frac{1 - \theta \beta (\Pi^r)^{\varepsilon-1}}{1 - \theta \beta (\Pi^r)^\varepsilon} \right) MC^r. \tag{C.3}$$

Second, the discounted sum of profits, given by

$$\Omega_{g,k}^r = \frac{1 - \theta_g^r \beta}{1 - \beta} \left[\sum_{k=0}^{\infty} (\beta \theta_g^r)^k \left[\left(\frac{\tilde{P}_g^*}{(\Pi^r)^k} \right)^{1-\varepsilon} - MC^r \left(\frac{\tilde{P}_g^*}{(\Pi^r)^k} \right)^{-\varepsilon} \right] - \omega \right] \tag{C.4}$$

is maximized by choosing θ_g^r , which results in $\tilde{P}_g^* = \tilde{P}^r$ and $\theta_g^r = \theta^r$, given that all other firms choose \tilde{P}^r and θ^r , according to a symmetric Nash equilibrium.

Furthermore, Calvo pricing leads to the following price dynamics due to $\theta_g^r = \theta^r$ and Eq. (C.2):

$$P_t^r = \left((1 - \theta^r) (\overline{P}_t^r)^{1-\varepsilon} + \theta^r (P_{t-1}^r)^{1-\varepsilon} \right)^{\frac{1}{1-\varepsilon}}.$$

This corresponds to the following steady-state expression:

$$\tilde{P}^r = \frac{\overline{P}^r}{P^r} = \left(\frac{1 - \theta^r (\Pi^r)^{\varepsilon-1}}{(1 - \theta^r)} \right)^{\frac{1}{1-\varepsilon}},$$

which can be combined with Eq. (C.3) to obtain an expression for steady-state marginal costs

$$MC^r = \left(\frac{\varepsilon - 1}{\varepsilon} \right) \left(\frac{1 - \theta^r \beta (\Pi^r)^\varepsilon}{1 - \theta^r \beta (\Pi^r)^{\varepsilon-1}} \right) \tilde{P}^{r*}, \tag{C.5}$$

Using Eq. (C.5), we can numerically solve θ^r through Eq. (C.4), given β and ω . Finally, for each region, we define the price dispersion across goods as follows:

$$\phi_t^r = var_g(\pi_{g,t}^r | r, t) = var_g(\log P_{g,t}^r - \log P_{g,t-1}^r | r, t), \tag{C.6}$$

which measures relative price variability (RPV) ϕ_t^r . To show the relation between ϕ_t^r and the inflation level, first define

$$\tilde{P}_t^r = E_g \log P_{g,t}^r, \tag{C.7}$$

which implies through Calvo pricing that

$$\begin{aligned} \tilde{P}_t^r - \tilde{P}_{t-1}^r &= E_g(\log P_{g,t}^r - \tilde{P}_{t-1}^r) \\ &= \theta^r E_g(\log P_{g,t-1}^r - \tilde{P}_{t-1}^r) + (1 - \theta^r)(\log \bar{P}_{g,t}^r - \tilde{P}_{t-1}^r) \\ &= (1 - \theta^r)(\log \bar{P}_{g,t}^r - \tilde{P}_{t-1}^r). \end{aligned} \tag{C.8}$$

Now, we can rewrite Eq. (C.6) as follows:

$$\begin{aligned} \phi_t^r &= \theta^r (\tilde{P}_{t-1}^r - \tilde{P}_{t-2}^r)^2 \\ &\quad + (1 - \theta^r) \theta^r E_g (\log \bar{P}_{g,t}^r - \log P_{g,t-2}^r - \tilde{P}_{t-1}^r + \tilde{P}_{t-2}^r)^2 \\ &\quad + (1 - \theta^r)^2 E_g (\log \bar{P}_{g,t}^r - \log \bar{P}_{g,t-1}^r - \tilde{P}_{t-1}^r + \tilde{P}_{t-2}^r)^2 \\ &\quad + (E_g \log P_{g,t}^r - E_g \log P_{g,t-1}^r - \tilde{P}_{t-1}^r + \tilde{P}_{t-2}^r)^2. \end{aligned}$$

Using Eqs. (C.7) and (C.8), it is further implied that

$$\phi_t^r = \theta^r (\tilde{P}_{t-1}^r - \tilde{P}_{t-2}^r)^2 + \theta^r \frac{(\tilde{P}_t^r - \tilde{P}_{t-1}^r)^2}{(1 - \theta^r)} + (1 - \theta^r) \theta^r \phi_{t-2}^r.$$

Finally, using the log-linear approximation of $\tilde{P}_t^r = \log P_t^r$, we obtain the following expression for relative price variability:

$$\phi_t^r = \theta^r (\pi_{t-1}^r)^2 + \theta^r \frac{(\pi_t^r)^2}{(1 - \theta^r)} + (1 - \theta^r) \theta^r \phi_{t-2}^r.$$

It is implied that in the steady state, we have

$$\phi^r = \frac{\theta^r (2 - \theta^r) (\pi^r)^2}{(1 - \theta^r + (\theta^r)^2) (1 - \theta^r)},$$

where as mentioned above, θ^r is numerically solved using Eq. (C.4), given β and ω .

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