Exchange Rate Pass-Through to Consumer Prices in Turkey: Nonparametric Kernel Estimation Evidence

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8 February 2021

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Summary of preliminary findings, contact the authors before citing

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Abstract

Exchange rate pass-through (ERPT) in the Turkish economy appeared again, especially after mid-2018 when policies to re-balance and soft-land the economy failed to a wide extent. Such re-appearance of the feedback from exchange rates to domestic prices deserves investigative efforts, having recalled that part of the stabilization success of the Central Bank of Turkey in early 2000s directly stemmed from its ability to reduce ERPT. In this paper, we aim to contribute to current policy discussions on Turkey by presenting our nonparametric kernel-based density function and regression estimates of the pass-through effect. Our findings are indicative not only of a sizable level of ERPT but also of its dependence on the size of currency depreciation.

Keywords: Exchange Rate, Currency Depreciation, Pass-through to Inflation, Consumer Prices, Monetary Policy, Inflation Targeting, Central Bank Performance.

JEL Codes: C51, E52, E58

1. Introduction

The definition of exchange rate pass-through (ERPT) diversifies regarding the strength of countries' economies, namely the emerging and advanced economies. ERPT is proposed as a percentage change in the exchange rate results in the percentage change in local currency import prices in advanced economies. However, ERPT in emerging economies is considered as the impact of a change in the foreign exchange rate on domestic prices. The phenomenon of ERPT is quite crucial in the sense that central banks efficiently impose macro policies in an inflationary environment, especially in the countries in which price stability is a chronic issue. Understandably, a low level of exchange rate pass-through generates a more independent monetary policy. Kara et al. (2007) suggested that the reasoning behind why domestic prices are affected in emerging markets is because they rely more on the imported intermediate goods in the production, hence one of the main differences reveals between the two definitions of ERPT.

Most emerging economies utilize the floating exchange rate regime and inflation targeting. As of the fact that Turkey is in the floating exchange rate regime since 2001, the exchange rate pass-through becomes a paramount subject to analyze the inflation dynamics. Monetary authorities in emerging markets have been feared that the unexpected volatility of exchange

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rate could imperil price stability. According to Ha et al. (2019), some countries have been taking action to prevent the undesirable fluctuations of the exchange rate, that is to say fear of floating, which can be reflected in ERPT. Another fact is that the implementation of inflation targeting initiates a room to eliminate the pressure of ERPT. According to Yüncüler (2011), after the adaptation of inflation targeting in Turkey, inflation started declining rapidly to levels as low as 5 percent. Caselli and Roitman (2016) also concluded that during the huge depreciation period, domestic prices react more negatively so that the amendatory impact of inflation targeting reduces the level of ERPT. Moreover, Patra et al. (2020) supported that the inflation targeting framework brings low and stable inflation across the emerging economies.

The vast majority of the literature on ERPT in emerging markets is about how such monetary policies could shape the relation between inflation and ERPT. Turkey, is being one of the emerging markets, shares similar dynamics with other emerging economies. A prominent factor is the use of monetary policy. Lopez and Mignon (2016) demonstrated that credibility and transparency of monetary policy decisions ease the catastrophic results of ERPT on domestic prices and they also mention the necessity of inflation targeting for stable price levels. Another study by Lamia et al. (2017) agrees upon the fact that monetary policy credibility and inflation targeting process have robust effects on lowering the degree of ERPT. From the perspective of most research, non-ITers and ITers indicate considerably distinctive outcomes for the inflationary environment.

Turkish literature also validates the parallel patterns of other emerging markets. What can be stated differently is that the weight of traded goods in the consumer basket is the critical aspect that makes the whole process problematic. Between January and September 2020, according to Broad Economic Classification (BEC), the ratio of the total imported intermediate goods is 75.4%. Kara et al. (2007) resulted in that because of the high weight of traded goods, during the 1990s, the period in which fixed/crawling peg exchange rate regime was implemented and high inflation was a major concern, price setters indexed their prices to the fluctuations in the exchange rate. The indexation problem led to ERPT negatively and stirred up inflation. On the other hand, the float period and implicit inflation targeting relieved the ERPT effect in Turkey. What is more, Kara and Öğünç (2007) deduced that two important factors might be valid to weaken the impact of ERPT: the role of inflation targeting in price setting and the decrease in the indexation. Furthermore, inflation expectations are worth mentioning to clarify another channel of forming ERPT. What Çiftçi and Yılmaz (2018) emphasized that immense ERPT not only propose cost-related outcomes but also by harming future expectations, they generate more considerable effects than cost effects. Henceforth, the expectations channel can build non-linear interactions between ERPT and inflation behavior. One last and broad study by Saygılı and Saygılı (2019) established that different industry features, such as the use of technology, degree of imported input use, and international trade connections are vital by the means of pass-through exchange rate on domestic prices.

The methodology that has been employed to investigate ERPT is quite ample. Kara and Öğünç (2007) used a monthly VAR model consisting of four variables that are output gap, import prices denominated in Turkish Lira, private manufacturing prices, and CPI excluding unprocessed food and administered prices; they examined the baseline model and impulse responses for both inflation targeting and non-targeting periods. Also, Kara et al. (2005) introduced a time-varying model with Kalman filter to point out that the degree of ERPT can reshape between regimes, through time, and between industries. Lamia et al. (2017) utilized a cointegrated VAR that granted them to seek the non-stationarity of the data consisting of 11 emerging markets. What Patra et al. (2020) aimed was to assess the dynamics of 15 emerging countries with a generic model proposed by Goldberg and Knetter (1997) regarding the role of monetary policy and adopting inflation targeting regime. A different approach was conducted by Önel and Goodwin (2013), that is nonparametric Generalized Additive Modeling to evaluate time-series data in a nonlinear fashion for three highly traded, homogeneous commodities affecting ERPT. A final methodological remark is about the nonparametric approach of Kernel density estimation. It has been handled in the literature since Rosenblatt (1956), estimates the density function at a place in which neighboring observations determine the results that are grounded on histogram methodology however to our knowledge, the method has not been managed for ERPT specifics (Zambom & Dias, 2013).

In this paper, we will estimate the effects of the exchange rate pass-through into the domestic prices in Turkey. The period is between the first quarter of 2005 and the first quarter of 2020. Two different time specifications will be conducted: monthly frequency and quarterly change; quarterly frequency and quarterly change for both the headline Consumer Price Index of Turkey and its 12 subgroups. For the sake of diversification of empirical analysis, parametric and nonparametric approaches will be employed. On one hand, ordinary least squares regression will be utilized for the parametric side. On the other hand, Kernel density regression analysis will be operated for the nonparametric approach purposes.

The remainder of the paper is structured as follows: Section 2 describes the empirical methodology; Section 3 provides our empirical specifications and Section 4 elaborates empirical findings against the recent economic history of Turkey. Section 5 concludes our work.

2. Methodology

As mentioned earlier, our preference toward nonparametric kernel estimation stems from a desire to liberate our analysis from functional forms. So, we want to come up with estimates that are not restricted to strict polynomial forms imposed for all sample points. In such an attempt to leave data to talk on its behalf, kernel smoothing techniques equip us with a toolset to obtain "one estimate for every given data point". In what follows, we briefly describe kernel smoothing, specifically referring to kernel density estimation and kernel regression cases.

As its name suggests, the essence of kernel smoothing is a mathematical object that we call the "kernel function", denoted $K(.)$. Function $K(.)$ is nonnegative and it returns a full set of weights for the observations of concern, at every observation it is evaluated. For any observation in a data set (call it the center), the weighting function $K(.)$ assigns the largest weight to the center where weights of other points are determined as a function to their distance to center. The kernel function can assume Gaussian, Triangular or Uniform shapes among many others. In our analysis, we maintain a second-order Gaussian kernel, so the weights display the shape of the normal probability distribution function.

"Assignment of weights to all data points evaluated at each data point" is key in nonparametric kernel estimation since our main goal while calculating our estimate is (1) to allow for a separate estimate at each data point and (2) to value the most the center compared to others while accounting for the others to a degree. Then it becomes critical how fast the weights decline as an observation falls far from the center. That speed of change of weights is controlled by a parameter called band width (or window width) where the argument of the function $K(.)$ is nothing but the distance between two points divided by band width. While the weights fall faster for a smaller band width, they fall slower for a larger band width. As a consequence, for a band width of zero only the center has a non-zero weight and for a band width of infinity every data point receives an equal weight. For the interested, while the former yields the data set itself as "the set of estimates", the latter gives us the popular Least Squares estimate at every data point.

Upon this semi-intuitive introduction via Kernel function, we can now describe our procedures to estimate densities and regression surfaces.

For a univariate, independent and identically distributed sample of n observations $\{X_i\}_{i=1}^{n}$, the kernel density estimator is given as:

$$\hat{f}_h(x) = \frac{1}{n}\sum_{i=1}^{n} K_h(x - X_i) = \frac{1}{nh}\sum_{i=1}^{n} K(\frac{x - X_i}{h}) \qquad (1)$$

where, $K(.)$ is the kernel function described above, x is the point at which we perform density estimation and h is the band width. The result of estimation here, $\hat{f}_h(x)$, is called the density ordinate at point x and it has the properties of a proper probability distribution function. Once plotted against its argument, $\hat{f}_h(x)$ provides us with the empirical distribution of the data under consideration.

Despite some additions, the main story of estimation is not altered for the case of nonparametric kernel regression. For a sample of n observations $\{(X_i, Y_i)\}_{i=1}^{n}$ where independent X_i and dependent Y_i are defined in R^d and R, respectively, a regression relationship can be written as (Hardle, 1990):

$$Y_i = m(X_i) + \epsilon_i \qquad (2)$$

where m is the unknown regression (mean) function and ϵ_i are the independent error terms with zero mean.

The local constant kernel regression, the local means of the dependent variable yield $\widehat{m}$ (Equation 3) by solving the problem in Equation 4 (Li and Racine, 2007).

$$\widehat{m}(x) = \frac{\sum_{i=1}^{n} Y_i K(\frac{x - X_i}{h})}{\sum_{i=1}^{n} K(\frac{x - X_i}{h})} \qquad (3)$$

$$\min_{a} \sum_{i=1}^{n} (Y_i - a)^2 K(\frac{x - X_i}{h}) \qquad (4)$$

K is the kernel (weight) function which is symmetric around zero with $lim|x|K(x) = 0$. The parameter h is known as window width (band width) and controls the smoothness of $\widehat{m}$ (Schimek, 2000). Intuitively, the problem is nothing but to obtain the averages of the dependent variables as fitted values. However, this problem entails two risks: a totally insufficient degree of smoothing, i.e. a window width of zero yields the observed values of the dependent variable as the fitted values and reflects full variance. The other extreme involves an infinite window width and so yield a constant fitted value at each observation, which is the case of full bias. Given a kernel function, the nonparametric kernel estimation is to find the fine line between variance and bias. This is achieved by solving for Equation 3 and 4. In many circumstances, local linear estimator in Equation 5 yield superior empirical outcomes:

$$\widehat{m}(x)=\frac{\sum_{i=1}^{n}Y_iK(\frac{x-X_i}{h})(s_{n,2}-(x-X_i)s_{n,1})}{n^{-2}+\sum_{i=1}^{n}K(\frac{x-X_i}{h})(s_{n,2}-(x-X_i)s_{n,1})}$$	(5)
$$s_{n,l}=\sum_{i=1}^{n}K(\frac{x-X_i}{h})(x-X_i)^l, l=0,1,2,\dots$$	
$$\min_{a,b}\sum_{i=1}^{n}\left(Y_i-a-b(x-X_i)'\right)^2K(\frac{x-X_i}{h})$$	(6)

This version of kernel regression has a slightly different intuition: one may imagine a least squares line segment within the window surrounding every single point of observation. A window of width h is located at each observation (call this observation of interest as center) and weights are assigned to full set of observations with respect to kernel function K, where weights are lower for observations more distant to center. Then a fitted value is computed for the center (see Hardle, 1990; Li and Racine, 2007; and Hardle et al., 2004).

Having obtained an estimate of the regression surface ($\widehat{m}$), the researcher can use it directly to make inferences about the variable of concern. Though, a richer set of findings can be achieved by calculating the empirical gradients, i.e. the response of $\widehat{m}$ to unit changes in its regressors:

$$\hat{\delta}(x_i)=\partial\widehat{m}(X)/\partial x_i$$	(7)

where $\widehat{m}(X)$ is the regression surface conditional on X and x_i is the regressor of concern. By design, the gradients are essentially the same thing as the coefficients in a typical (linear or nonlinear) least squares regression setup. For instance, when the regression surface and the regressors are both in percentages or percent changes, the gradients turn out to be elasticities. A major difference as to gradient estimates of the nonparametric kernel regression is that they are byproducts of surface estimation problem rather than being directly estimable objects.

3. Empirical Framework

a. Specifications

Using the technical background presented in the previous section, we provide the following set of specifications here. In order to save some space and to avoid a mess of notation, we briefly list those specifications as:

(1) Inflation as a nonparametric function of depreciation (Inflation ~ Depreciation)

a. Monthly data frequency and quarterly variable measurements: Conditional densities (Figure 1), Gradients (Figure 2)

b. Quarterly data frequency and quarterly variable measurements: Conditional densities (Figure 3), Gradients (Figure 4)

(2) "Inflation net of its lagged effect" as a nonparametric function of depreciation

a. Monthly data frequency and quarterly variable measurements: Conditional densities (Figure 5), Gradients (Figure 6)

b. Quarterly data frequency and quarterly variable measurements: Conditional densities (Figure 7), Gradients (Figure 8)

(3) Parametric (LS) models: Inflation as a function of lagged inflation, current depreciation and lagged depreciation

  a. Monthly data frequency and quarterly variable measurements (Table 5)

  b. Quarterly data frequency and quarterly variable measurements (Table 6)

The reader would notice that, apart from data frequencies, 1b and 2b are the same as 1a and 2a, respectively. 1a and 1b simply follow the traditional ERPT specifications of the literature. 2a and 2b, on the other hand, are slightly unconventional since we follow a two-step approach in these. In each, we first estimate a simple LS regression of inflation on its lagged value and calculate inflation net of its own inertia. In the second step, we nonparametrically estimate a surface for this new variable as a function of depreciation alone.

In a nutshell, our specifications have been designed to provide a rich overview of the ERPT behavior, as discussed in section 4.

b. Data

The data set was compiled from the Electronic Data Delivery System of the Central Bank of the Republic of Turkey and from TurkStat. Consumer Price Index and its twelve main subgroups (2003=100) have been subject to seasonal adjustment whenever necessary, while period averages of the Turkish lira value of the US dollar and EURO were originally maintained in the analysis. Inflation and depreciation rates were calculated as percentage changes of those.

4. Estimates and Discussion

Having computed our nonparametric estimates using the 'np' package for R by Racine and Hayfield (2020, Version 0.60-10), we reached some regularities. Focusing on quarterly data specifications only, we reveal an observable degree of ERPT from depreciation to inflation as suggested by Figure 4. For the 'headline CPI', 'food and non-alcoholic beverages', 'housing, water, electricity, gas and other fuels', 'furnishing, household equipment, routine maintenance of the house', 'communications', 'recreation and culture', 'hotels and restaurants' and 'miscellaneous goods and services', the measured ERPT effects are increasing in depreciation rate. So, not only there occurs ERPT but also is the size of impact magnified for higher rates of currency depreciation, i.e., price setters seem not to have taken swift action until they observe a serious degree of depreciation.

In Figure 4, for 'alcoholic beverages and tobacco', 'clothing and footwear' and 'transportation', there is positive ERPT without dependence on the magnitude of depreciation. In mechanical terms, the band widths for these items turn out to be infinite (practically too large), so the nonparametric kernel regression boils down to a standard LS regression. While the ERPT behavior as a function depreciation remains mixed for 'health', there is an inverted U-shaped behavior in the case of 'education'.

Moving to Figure 8, where we report the same using our two-step approach, we reveal that positive ERPT for all the inflation items considered. In the cases of "food and non-alcoholic beverages', 'housing, water, electricity, gas and other fuels', 'communication' and 'miscellaneous goods and services', the size of ERPT increases in depreciation. For 'clothing and footwear' and 'education' the size of ERPT decreases in depreciation, though. The other items display a positive yet depreciation-invariant degree of ERPT.

It may be a little harder to establish the exact same conclusions based on monthly data specifications for a couple of reasons. In that, reflection of depreciation rate on the rate of change of prices may be limited at a monthly frequency. Even if we could handle the issue by including lagged values of depreciation, our nonparametric kernel framework turns out to be not generous in terms of allowing for many lagged values of explanatory variables, especially in the absence of substantially larger samples. Still, monthly results are provided in Figure 2 and Figure 6 for the interested reader.

Eventually, our analysis reveals not only the existence of a nonnegligible degree of ERPT, but also it underlines the dependence of the estimated ERPT effects on the magnitude of currency depreciation. So, the salutary picture drawn by Kara et al. (2007) and Kara and Ogunc (2007) seems valid no more. Despite the latter was not so optimistic, a common denominator of these papers was that they both reported a visibly lowered ERPT behavior for Turkey's economy. Indeed, they were quite reflecting the reality at that time. If we recall, in the aftermath of the 2001 Financial Crisis, Turkey's government officials implemented a serious stabilization program sponsored by the International Monetary Fund. In addition to several changes in fiscal policy and an array of promises for micro-reforms, in the monetary front, the Central Bank of Turkey (CBT) began implementing an implicit inflation targeting framework supported by the legislation of a new Central Bank Law that brought central bank independence (Law No. 1211, January 14, 1970 amended by Law No. 4651, April 25, 2001). Following the successful disinflation of 2001-2005, effective upon January 2006 the Bank extended its policy framework into explicit (full-fledged) inflation targeting. However, leaving the several political details aside, this success seems discontinued after nearly two decades. Specifically, the construction-oriented growth of Turkey after the Global Financial Crises yielded sufficiently high economic growth rates, yet it lacked the ability to generate sufficient foreign exchange reserves. After the slowdown in construction by the end-2017, the derailing of the currency as well as inflation after mid-2018 was not surprising. In this shifted climate, a big portion of inflation was often attributed to currency depreciation. Equivalently, the disinflation induced by currency appreciation in the 2000s seems to have been taken back by 2020.

5. Concluding Remarks

'So what?' is the last question that needs an answer once it was noted above that ERPT has still been an important mechanism in the making of domestic price dynamics. The first suggestion is that monetary policy framework should be set free of short-termist political pressures. This is not different than suggesting a restoration of the Central Bank's independence to the fullest extent, as well-described in the inflation targeting literature. In such an environment, a successful conduct of the exchange rate policy would yield satisfactory inflation outcomes.

The second suggestion, on the other hand, points at more and well-orchestrated efforts to reduce import-dependence in domestic production as well as several provisions to find the optimal split between market regulation/deregulation. In fact, a number of promises toward these ends are already available in the micro reform agenda of the post-2001 crisis. So, observing our scope here, we suffice with pointing at these rather than speculating.

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Guide to Read the Visuals

In the upcoming pages a sequence of estimates is visualized. The set of graphs comprise of (1) Kernel density estimates, (2) Kernel gradient estimates. The set of tables, on the other hand, contain auxiliary information that is more informative for the interested reader. The reader is advised to keep in mind the following while observing the presented findings:

(1) Kernel density estimates: the vertical axis shows the kernel density ordinates (simply the Probability Distribution Function values). On the horizontal plane, the axis extending toward the reader shows increasing currency depreciation and the axis parallel to page shows inflation rate (increasing from left to right). So, the figure provides multiplicity of density functions of inflation together as a surface, where the projections closer to the reader are estimated at higher rates of currency depreciation. In Section 2's terms, density ordinates are those $\hat{f}(\cdot)$ figures.

(2) Kernel gradient estimates: the vertical axis shows the kernel gradient estimates against the horizontal axis of currency depreciation. So, kernel gradient graphs simply display the ERPT as an empirical function of depreciation. In Section 2's terms, gradients are those $\hat{\delta}(\cdot)$ values.

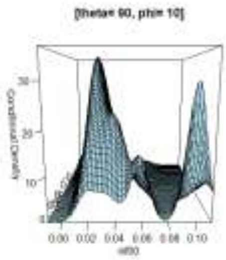
(3) For each group of nonparametric kernel estimates, the band widths and the coefficients of determination are summarized in a table.

(4) The last four tables provide the simple LS estimates for ERPT equations. Note that these tables are to give some rough information only.

As we want to provide the reader as much visual information as possible, the figures are very crowded in a way to impede visual perception. For better utilization of those, viewing the figures and reading the paper on a large-screen device rather than a smart phone is kindly advised.

Figure 1. Nonparametric Kernel Conditional Density Estimates,
Inflation ~ Depreciation, Monthly Data, Quarterly Inflation and Depreciation

Headline CPI



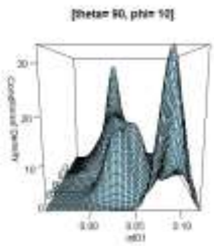
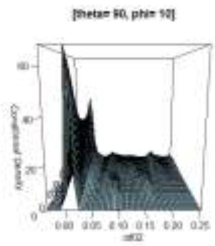
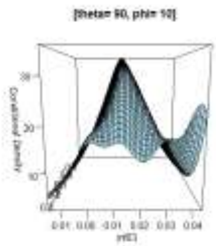
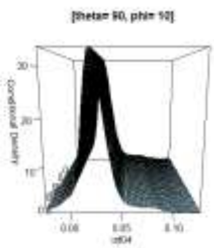
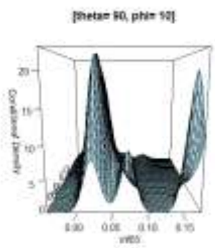
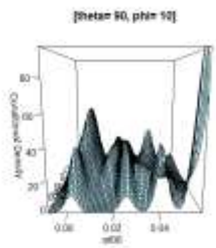
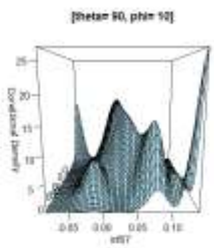
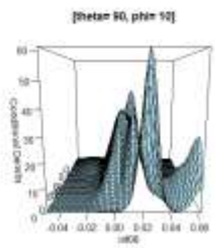
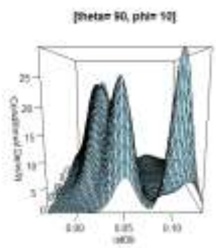
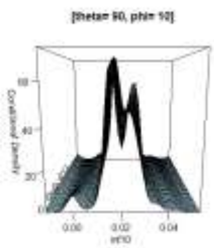
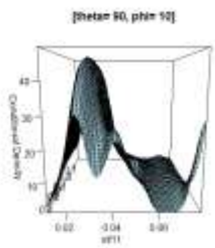
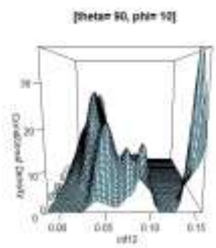
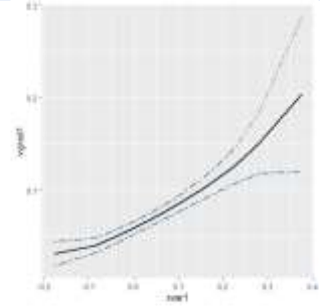
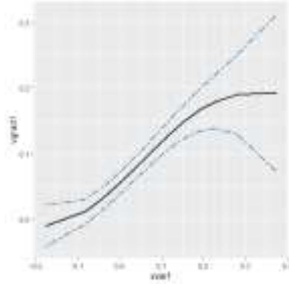
FOOD/NON-ALCOHOLIC BEVERAGES	ALCOHOLIC BEVERAGES/TOBACCO	CLOTHING/FOOTWEAR
		
HOUSING/WATER/ELECTRICITY/ GAS/ OTHER FUELS	**FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE**	**HEALTH**
		
TRANSPORT	**COMMUNICATIONS**	**RECREATION/CULTURE**
		
EDUCATION	**HOTELS/CAFES/RESTAURANTS**	**MISCELLANEOUS GOODS AND SERVICES**
		

Figure 2. Nonparametric Kernel Gradient Estimates, Inflation ~ Depreciation, Monthly Data, Quarterly Inflation and Depreciation

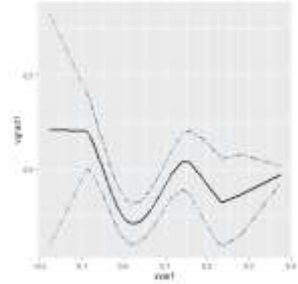
Headline CPI



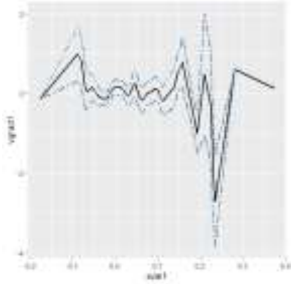
FOOD/NON-ALCOHOLIC BEVERAGES



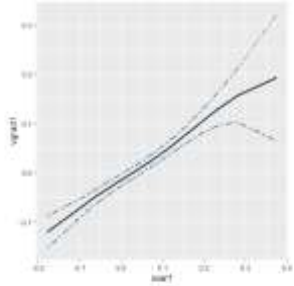
ALCOHOLIC BEVERAGES/TOBACCO



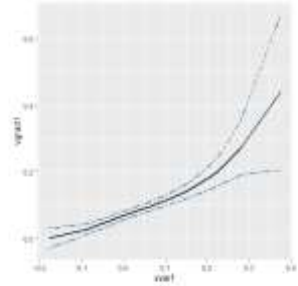
CLOTHING/FOOTWEAR



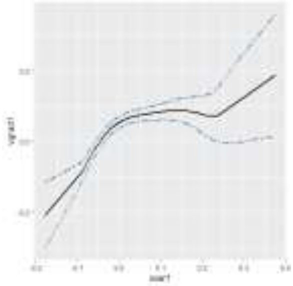
HOUSING/WATER/ELECTRICITY/ GAS/ OTHER FUELS



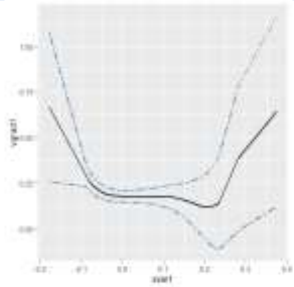
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE



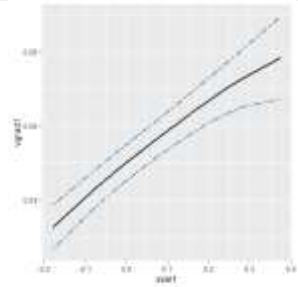
HEALTH



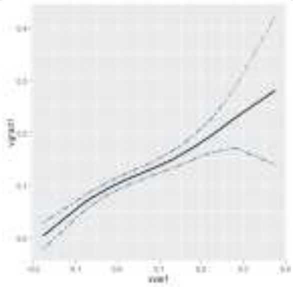
TRANSPORT



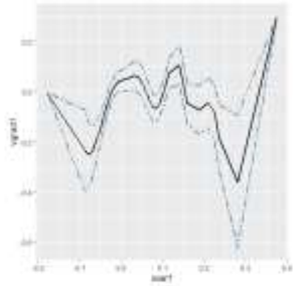
COMMUNICATIONS



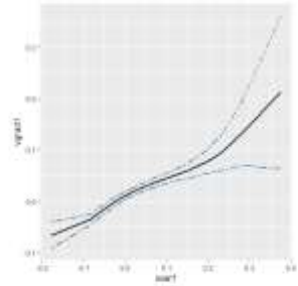
RECREATION/CULTURE



EDUCATION



HOTELS/CAFES/RESTAURANTS



MISCELLANEOUS GOODS AND SERVICES

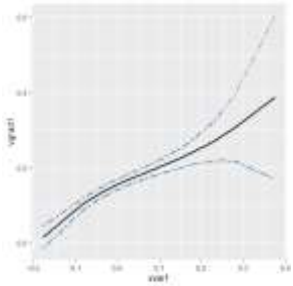


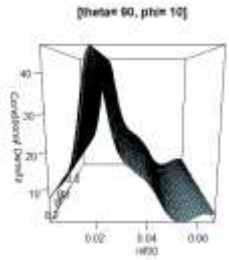
Table 1. Nonparametric Kernel Model Summary
Monthly Data and Quarterly Changes

Model01: Inflation ~ Depreciation

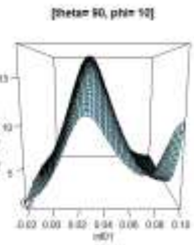
Subgroup	BW (Dep)	R^2
Headline CPI	0.11743	0.313
FOOD/NON-ALCOHOLIC BEVERAGES	0.10705	0.134
ALCOHOLIC BEVERAGE/TOBACCO	0.04815	0.045
CLOTHING/FOOTWEAR	0.00943	0.144
HOUSING/WATER/ELECTRICITY/GAS/OTHER FUELS	0.10033	0.150
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE	0.10342	0.306
HEALTH	0.06406	0.187
TRANSPORT	0.05412	0.332
COMMUNICATIONS	0.19806	0.099
RECREATION/CULTURE	0.10444	0.336
EDUCATION	0.02092	0.137
HOTELS/CAFES/RESTAURANTS	0.08129	0.262
MISCELLANEOUS GOODS AND SERVICES	0.09599	0.459

**Figure 3. Nonparametric Kernel Conditional Density Estimates,
Inflation ~ Depreciation, Quarterly Data, Quarterly Inflation and Depreciation**

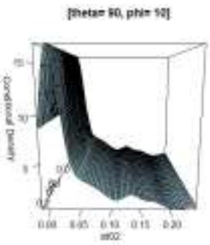
Headline CPI



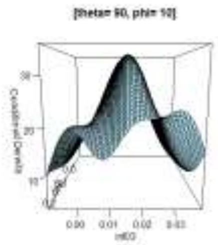
FOOD/NON-ALCOHOLIC BEVERAGES



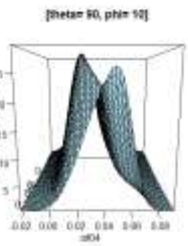
ALCOHOLIC BEVERAGES/TOBACCO



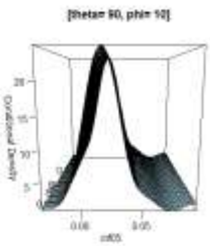
CLOTHING/FOOTWEAR



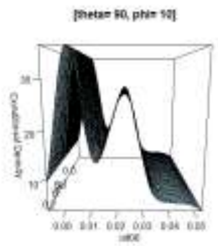
HOUSING/WATER/ELECTRICITY/ GAS/ OTHER FUELS



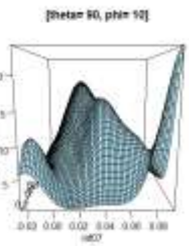
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE



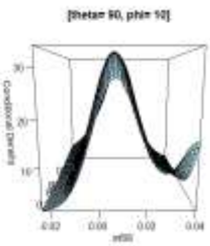
HEALTH



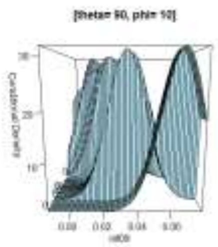
TRANSPORT



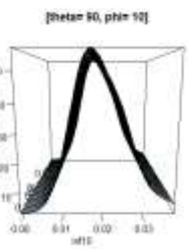
COMMUNICATIONS



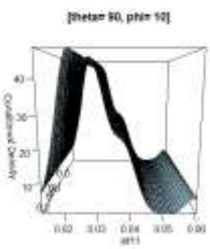
RECREATION/CULTURE



EDUCATION



HOTELS/CAFES/RESTAURANTS



MISCELLANEOUS GOODS AND SERVICES

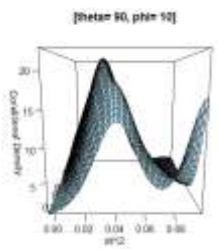
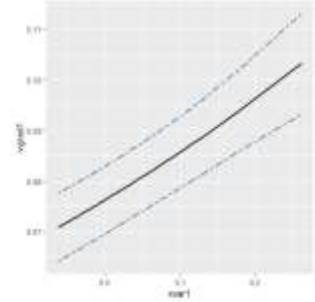
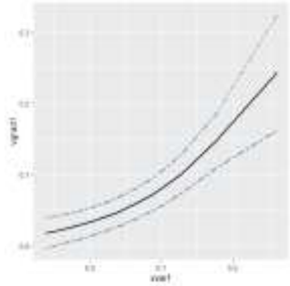


Figure 4. Nonparametric Kernel Gradient Estimates, Inflation ~ Depreciation, Quarterly Data, Quarterly Inflation and Depreciation

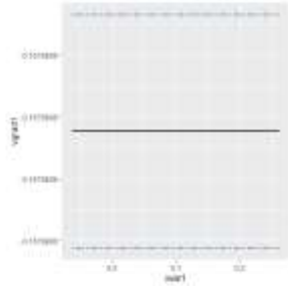
Headline CPI



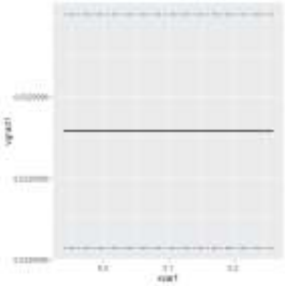
FOOD/NON-ALCOHOLIC BEVERAGES



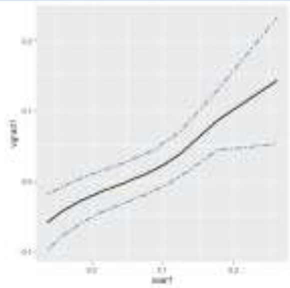
ALCOHOLIC BEVERAGES/TOBACCO



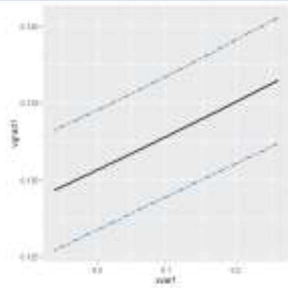
CLOTHING/FOOTWEAR



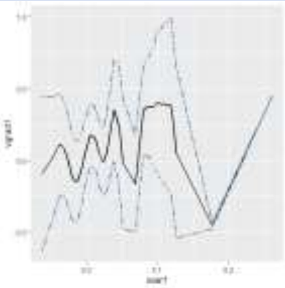
HOUSING/WATER/ELECTRICITY/ GAS/ OTHER FUELS



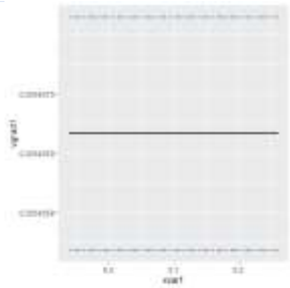
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE



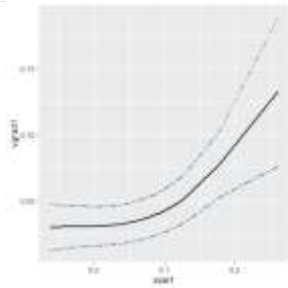
HEALTH



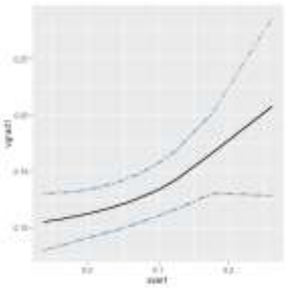
TRANSPORT



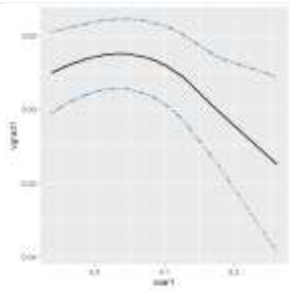
COMMUNICATIONS



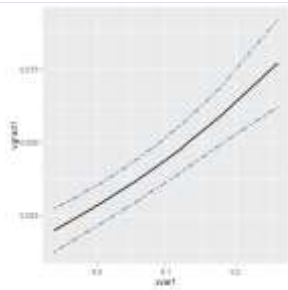
RECREATION/CULTURE



EDUCATION



HOTELS/CAFES/RESTAURANTS



MISCELLANEOUS GOODS AND SERVICES

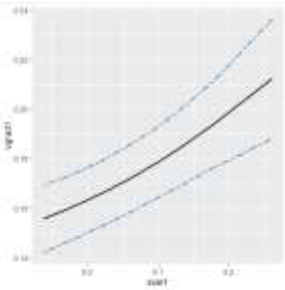


Table 2. Nonparametric Kernel Model Summary Quarterly Data and Quarterly Changes		
Model02: Inflation ~ Depreciation		
Subgroup	**BW (Dep)**	**R^2**
Headline CPI	0.21404	0.202
FOOD/NON-ALCOHOLIC BEVERAGES	0.11077	0.220
ALCOHOLIC BEVERAGE/TOBACCO	672235	0.035
CLOTHING/FOOTWEAR	438093	0.034
HOUSING/WATER/ELECTRICITY/GAS/OTHER FUELS	0.07770	0.064
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE	0.60776	0.161
HEALTH	0.01208	0.213
TRANSPORT	559759	0.280
COMMUNICATIONS	0.09757	0.146
RECREATION/CULTURE	0.09522	0.273
EDUCATION	0.09428	0.016
HOTELS/CAFES/RESTAURANTS	0.14902	0.163
MISCELLANEOUS GOODS AND SERVICES	0.17227	0.322

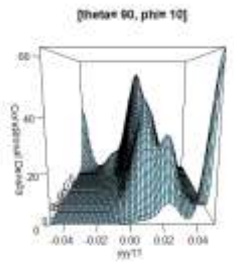
Figure 5. Nonparametric Kernel Conditional Density Estimates

Step 1: Inflation ~ Inflation Lag (OLS Regression) $\rightarrow$ $\bar{\alpha}_{OLS}$

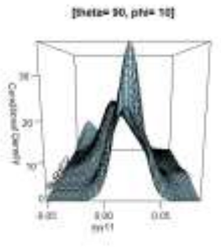
Step 2: Inflation$_1$ = Inflation – $\bar{\alpha}_{OLS}$ * Inflation Lag ~ Depreciation (Kernel Regression)

Monthly Data, Quarterly Inflation and Depreciation

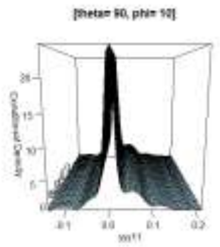
Headline CPI



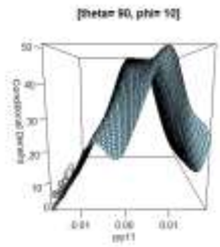
FOOD/NON-ALCOHOLIC BEVERAGES



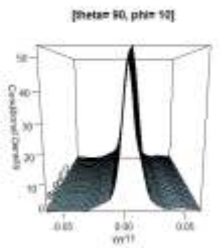
ALCOHOLIC BEVERAGES/TOBACCO



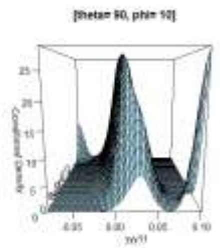
CLOTHING/FOOTWEAR



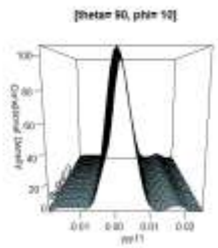
HOUSING/WATER/ELECTRICITY/ GAS/ OTHER FUELS



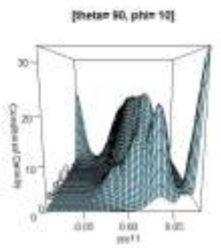
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE



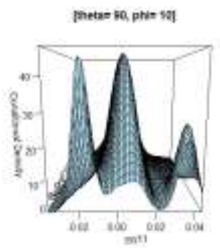
HEALTH



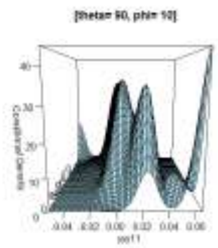
TRANSPORT



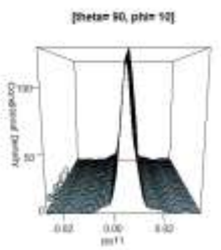
COMMUNICATIONS



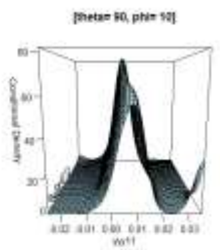
RECREATION/CULTURE



EDUCATION



HOTELS/CAFES/RESTAURANTS



MISCELLANEOUS GOODS AND SERVICES

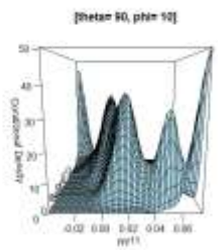


Figure 6. Nonparametric Kernel Gradient Estimates

Step 1: Inflation ~ Inflation Lag (OLS Regression) $\rightarrow$ $\bar{\alpha}_{OLS}$

Step 2: Inflation_1 = Inflation – $\bar{\alpha}_{OLS}$ * Inflation Lag ~ Depreciation (Kernel Regression)

Monthly Data, Quarterly Inflation and Depreciation

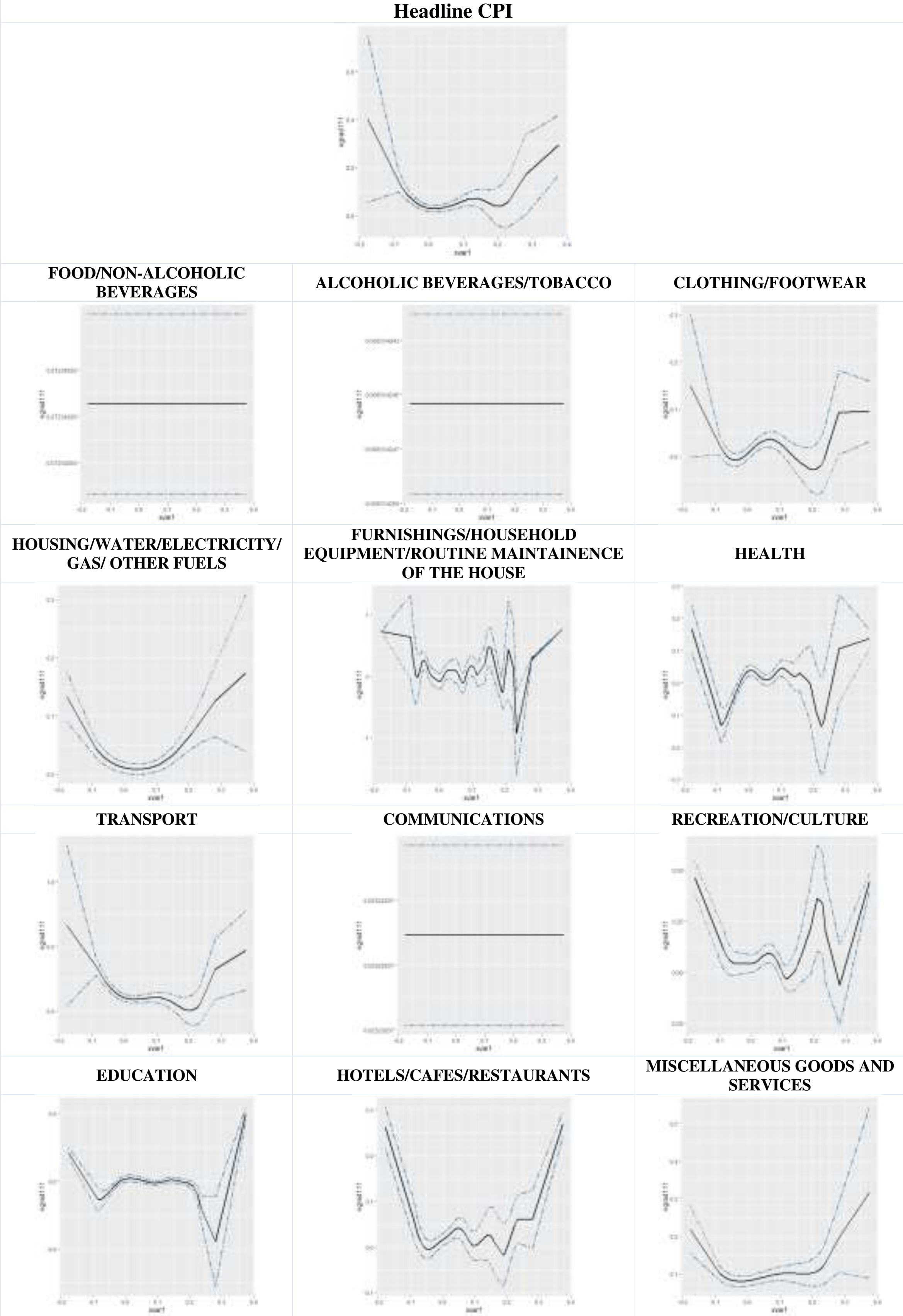


Table 3. Nonparametric Kernel Model Summary Monthly Data and Quarterly Changes		
Model02: $Inflation_1 \sim Depreciation$		
Subgroup	**BW (Dep)**	**R^2**
Headline CPI	0.03580	0.552
FOOD/NON-ALCOHOLIC BEVERAGES	1414102	0.068
ALCOHOLIC BEVERAGE/TOBACCO	947064	0.00012
CLOTHING/FOOTWEAR	0.04492	0.115
HOUSING/WATER/ELECTRICITY/GAS/OTHER FUELS	0.08213	0.166
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE	0.01150	0.553
HEALTH	0.02897	0.196
TRANSPORT	0.04555	0.385
COMMUNICATIONS	1030659	0.026
RECREATION/CULTURE	0.02507	0.404
EDUCATION	0.02500	0.286
HOTELS/CAFES/RESTAURANTS	0.02500	0.454
MISCELLANEOUS GOODS AND SERVICES	0.07022	0.370

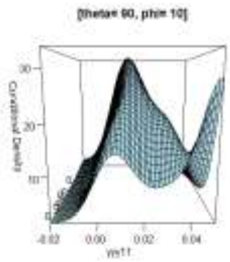
Figure 7. Nonparametric Kernel Conditional Density Estimates

Step 1: Inflation ~ Inflation Lag (OLS Regression) $\rightarrow$ $\bar{\alpha}_{OLS}$

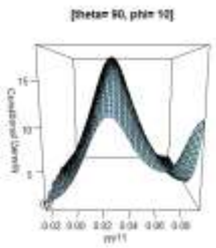
Step 2: Inflation$_1$ = Inflation – $\bar{\alpha}_{OLS}$ * Inflation Lag ~ Depreciation (Kernel Regression)

Quarterly Data, Quarterly Inflation and Depreciation

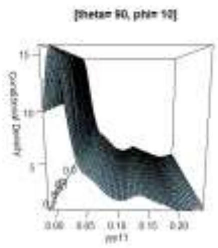
Headline CPI



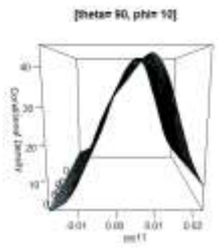
FOOD/NON-ALCOHOLIC BEVERAGES



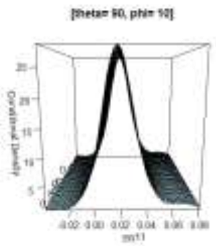
ALCOHOLIC BEVERAGES/TOBACCO



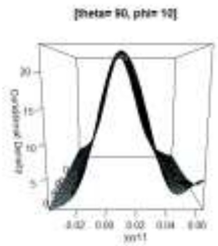
CLOTHING/FOOTWEAR



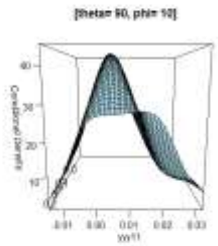
HOUSING/WATER/ELECTRICITY/ GAS/ OTHER FUELS



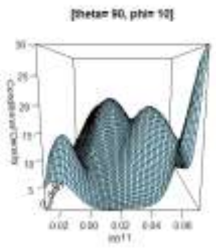
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE



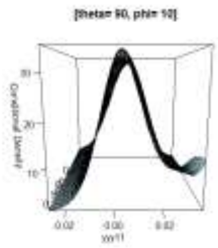
HEALTH



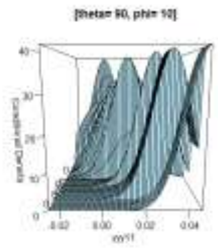
TRANSPORT



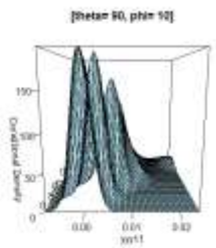
COMMUNICATIONS



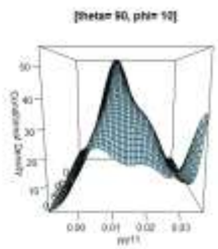
RECREATION/CULTURE



EDUCATION



HOTELS/CAFES/RESTAURANTS



MISCELLANEOUS GOODS AND SERVICES

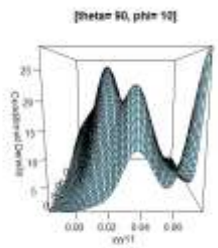


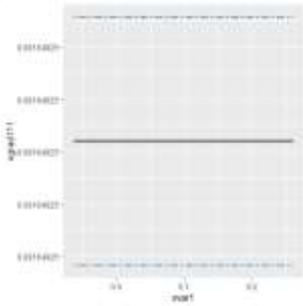
Figure 8. Nonparametric Kernel Gradient Estimates

Step 1: Inflation ~ Inflation Lag (OLS Regression) $\rightarrow$ $\bar{\alpha}_{OLS}$

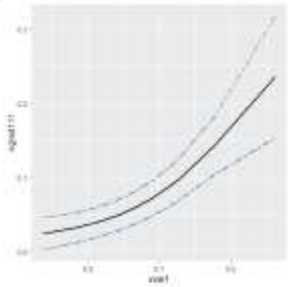
Step 2: $Inflation_1$ = Inflation – $\bar{\alpha}_{OLS}$ * Inflation Lag ~ Depreciation (Kernel Regression)

Quarterly Data, Quarterly Inflation and Depreciation

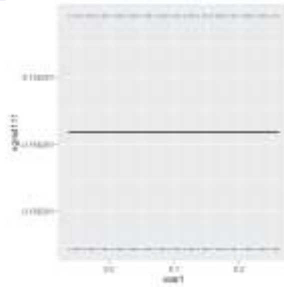
Headline CPI



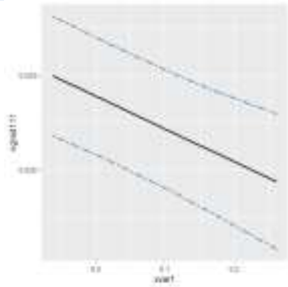
FOOD/NON-ALCOHOLIC BEVERAGES



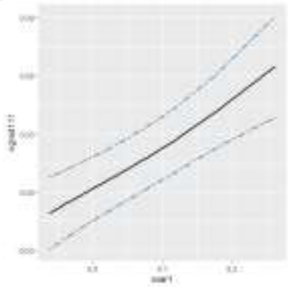
ALCOHOLIC BEVERAGES/TOBACCO



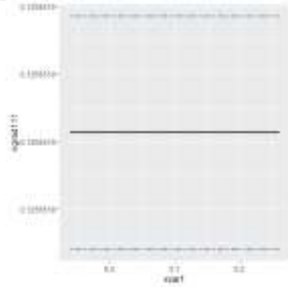
CLOTHING/FOOTWEAR



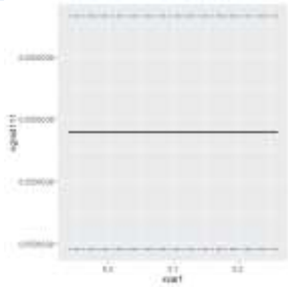
HOUSING/WATER/ELECTRICITY/ GAS/OTHER FUELS



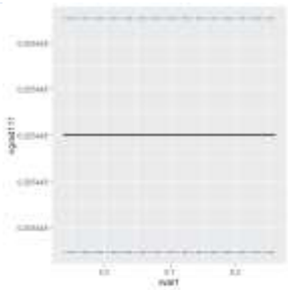
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE



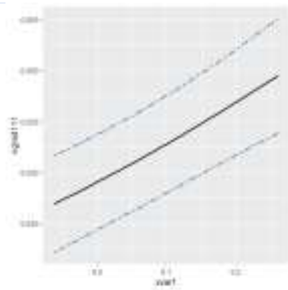
HEALTH



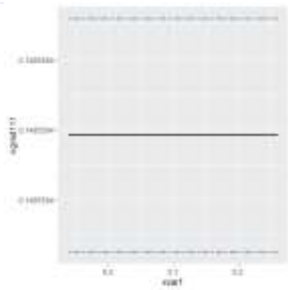
TRANSPORT



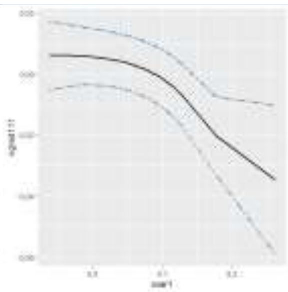
COMMUNICATIONS



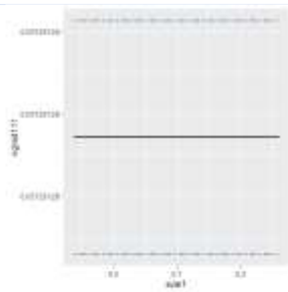
RECREATION/CULTURE



EDUCATION



HOTELS/CAFES/RESTAURANTS



MISCELLANEOUS GOODS AND SERVICES

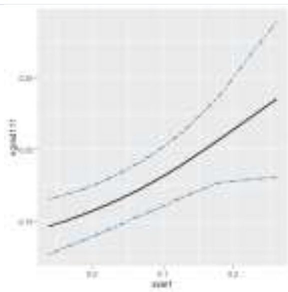


Table 4. Nonparametric Kernel Model Summary Quarterly Data and Quarterly Changes		
Model02: $Inflation_1 \sim Depreciation$		
Subgroup	**BW (Dep)**	**R^2**
Headline CPI	585002	0.224
FOOD/NON-ALCOHOLIC BEVERAGES	0.11002	0.207
ALCOHOLIC BEVERAGE/TOBACCO	1479218	0.031
CLOTHING/FOOTWEAR	0.30117	0.033
HOUSING/WATER/ELECTRICITY/GAS/OTHER FUELS	0.13349	0.035
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE	11661297	0.201
HEALTH	2095055	0.137
TRANSPORT	2104393	0.308
COMMUNICATIONS	0.29397	0.088
RECREATION/CULTURE	531845	0.361
EDUCATION	0.07480	0.036
HOTELS/CAFES/RESTAURANTS	15376231	0.222
MISCELLANEOUS GOODS AND SERVICES	0.11775	0.388

Table 5. Parametric Models with Monthly Data and Quarterly Changes

OLS MODEL01: $inf_t = \varphi + \alpha_1 inf_{t-1} + \beta_0 dep_t + \beta_1 dep_{t-1} + \varepsilon_t$

Subgroup	Inflation Lag Coefficient	Depreciation Coefficient	Depreciation Lag Coefficient	R^2 Adj-R^2
Headline CPI	0.773 (18.132)	0.082 (7.503)	-0.014 (-1.106)	0.782 (0.779)
FOOD/NON-ALCOHOLIC BEVERAGES	0.608 (10.439)	0.072 (2.424)	0.003 (0.112)	0.456 (0.447)
ALCOHOLIC BEVERAGE/TOBACCO	0.672 (11.875)	0.043 (0.646)	-0.068 (-1.023)	0.455 (0.446)
CLOTHING/FOOTWEAR	0.779 (17.532)	0.013 (1.231)	0.011 (1.064)	0.662 (0.657)
HOUSING/WATER/ELECTRICITY/GAS/OTHER FUELS	0.748 (15.718)	0.026 (1.501)	0.029 (1.594)	0.630 (0.623)
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE	0.724 (16.509)	0.084 (4.378)	0.029 (1.383)	0.742 (0.737)
HEALTH	0.907 (32.391)	0.016 (1.979)	0.006 (0.707)	0.873 (0.871)
TRANSPORT	0.730 (14.296)	0.192 (7.598)	-0.080 (-2.760)	0.690 (0.685)
COMMUNICATIONS	0.654 (11.496)	0.033 (2.097)	-0.012 (-0.724)	0.479 (0.470)
RECREATION/CULTURE	0.689 (14.390)	0.095 (5.735)	0.004 (0.215)	0.727 (0.722)
EDUCATION	0.712 (13.976)	-0.019 (-2.274)	0.028 (3.333)	0.540 0.532)
HOTELS/CAFES/RESTAURANTS	0.830 (22.369)	0.037 (5.243)	-0.004 (-0.526)	0.795 (0.792)
MISCELLANEOUS GOODS AND SERVICES	0.746 (15.946)	0.175 (9.962)	-0.075 (-3.561)	0.774 (0.771)

Values in parentheses indicate t-stats.

Table 6. Parametric Models with Quarterly Data and Quarterly Changes				
OLS MODEL01: $inf_t = \varphi + \alpha_1 inf_{t-1} + \beta_0 dep_t + \beta_1 dep_{t-1} + \varepsilon_t$				
Subgroup	**Inflation Lag Coefficient**	**Depreciation Coefficient**	**Depreciation Lag Coefficient**	**R^2 Adj-R^2**
Headline CPI	0.277 (2.370)	0.085 (3.827)	0.055 (2.251)	0.389 (0.355)
FOOD/NON-ALCOHOLIC BEVERAGES	0.005 (0.046)	0.097 (2.367)	0.091 (2.106)	0.178 (0.133)
ALCOHOLIC BEVERAGE/TOBACCO	0.015 (0.108)	-0.164 (-1.342)	-0.039 (-0.322)	0.038 (-0.01)
CLOTHING/FOOTWEAR	0.590 (6.274)	0.019 (1.135)	0.039 (2.340)	0.500 (0.473)
HOUSING/WATER/ELECTRICITY/GAS/OTHER FUELS	0.165 (1.282)	0.018 (0.474)	0.072 (1.887)	0.102 (0.053)
FURNISHINGS/HOUSEHOLD EQUIPMENT/ROUTINE MAINTAINENCE OF THE HOUSE	0.409 (4.085)	0.116 (3.738)	0.112 (3.304)	0.540 (0.515)
HEALTH	0.747 (10.549)	0.047 (2.949)	0.049 (2.941)	0.754 (0.741)
TRANSPORT	0.330 (2.610)	0.207 (4.961)	-0.018 (-0.371)	0.377 (0.343)
COMMUNICATIONS	0.239 (1.857)	0.053 (2.142)	0.022 (0.855)	0.175 (0.130)
RECREATION/CULTURE	0.314 (3.365)	0.134 (5.792)	0.117 (4.347)	0.646 (0.626)
EDUCATION	0.726 (7.898)	-0.009 (-0.863)	0.026 (2.492)	0.559 (0.535)
HOTELS/CAFES/RESTAURANTS	0.569 (5.889)	0.054 (3.804)	0.028 (1.857)	0.534 (0.508)
MISCELLANEOUS GOODS AND SERVICES	0.317 (2.695)	0.181 (5.514)	0.053 (1.338)	0.482 (0.454)
Values in parentheses indicate t-stats.				