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Import Tariff Pass-through Effect and the Spatial Distribution of Domestic Consumer Goods Prices: Zimbabwe (2009-2014) *

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Abstract

The study of import tariffs pass-through has been observed to be crucial for policy making, for instance, this may inflate some goods' prices thus harming individual welfare. However, the extant literature on the import tariffs pass-through effect has largely ignored the possibility of spatial dependence between domestic goods prices which may brew imprecise estimates. Hence, this study proposes an extension of the traditional empirical model for estimating the import tariff pass-through effect by introducing controls for the domestic spatial dependence of prices. The estimates rely on a panel dataset of consumer goods for Zimbabwe, which has both the individual and time spatial effects. The spatial econometrics model used in this study all agree that there is positive spatial dependence of domestic goods' prices in Zimbabwe over the period 2009 to 2014. When compared to our modified model, the traditional import tariffs pass-through model was found to highly overestimate the import tariffs pass-through effect. The study found that a positive and significant portion of import tariffs is being passed on to domestic goods prices in Zimbabwe. Thus, there is a need for policy to be cautious of the import tariffs increase in relationship to national inflation, and poverty targets.

Key words: spatial dependence, import tariffs pass-through, Consumer Goods Prices

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1 Introduction

The impact of import tariffs on domestic goods prices has long been receiving attention in international trade literature (c.f. Brander and Spence, 1984; Feenstra, 1989; Mallick and Marques, 2007; Han et al, 2016; Hayakawa and Ito, 2015; Ludema and Yu, 2016). It is well-known as the pass-through effect (ITPTE hereafter)[2]. The accorded scholarly attention has been associated with the welfare effects of international trade under the terms of trade argument (Feenstra, 2015). For instance, in the context of imperfect competition, Brander and Spence (1984) theoretically asserted that if an importing country imposes a tariff on a product the exporting country may reduce its export price, to gain a larger market in the foreign country. By implication, the exporter absorbs part of the tariff (partial pass-through) which culminates in terms of trade gain for the importing country (Brander and Spence, 1984, Feenstra, 2003 p.305; Hayakawa and Ito, 2015). In turn, the ITPTE may intricately affect real economic variables like inflation, factor returns, industrialisation, economic growth and household welfare (Ahn and Park, 2014; Feenstra, 1989; Kreinin 1977; Mallick and Marques, 2007; Cavallo et al., 2021). Consequently, economic development imperatives have made the topic of interest to many scholars and policy analysts, especially in developed countries (c.f., Feenstra, 1989; Mallick and Marques, 2007; Han et al., 2016; Hayakawa and Ito, 2015; Ludema and Yu, 2016). This policy relevance highlights the importance of precise estimates of the ITPTE.

Existing studies of the ITPTE have been carried out at the national, industry and firm-level (e.g), Hayakawa and Ito, 2015; Feenstra, 1989; Mallick and Marques, 2007; Hayakawa and Ito 2015). This paper seeks to expand the ITPTE literature through undertaking ITPTE at regional level within a country using product level dataset. The most common finding is that of an incomplete rather than a complete ITPTE. However, the size of the estimates varies with context, for instance, Feenstra (1989) found a complete ITPTE ranging from 94.9-138.8 percent for Japanese motorcycles imported in the United States of America (USA), and 60 percent for Japanese trucks. Hayakawa and Ito (2015) found an average incomplete ITPTE ranging from 28.2–72.7 percent for countries such as Singapore, Japan, Italy, France, among others.

[2] The ITPTE ranges from an incomplete to a complete pass through effect. An incomplete import tariffs pass through effect means that a change in import tariff will result in a small effect on domestic goods prices. A complete pass through implies that, for example a 10 percent increase in import tariffs will also result in a 10 percent increase in domestic goods prices - entire change in import tariffs is passed on to domestic goods prices.

Although all previous studies are informative, their estimates may be compromised by the underlying regression models' failure to control for the nature of price distribution at the estimation level of the ITPTE. As an example, for an ITPTE estimated at the regional level the regression model's dependent variable 'domestic goods price', can be randomly distributed or autocorrelated across regions - positive or negatively. A random price distribution implies independence of goods prices across regions. Positive (negative) spatial autocorrelation means that prices in one region are positively (negatively) linked to prices in proximate regions. Thus, the existing studies' estimates of the ITPTE could be biased by an 'omitted variable problem'[3] should domestic goods prices be positively (negatively) autocorrelated. The severity of the omitted variable bias is highlighted in Wooldridge (2002); Green (2012) and Clarke (2005).
In cases of a random price distribution, a change in import tariffs is likely to affect regional prices independently without a second-round effect; due to lack of spatial price correlation (Beag and Singla, 2014). When there is spatial autocorrelation, an import tariffs change may have second and third-round effects on domestic goods prices due to the regional price linkages (Sekhar, 2012). The latter implies that more precise estimates of the ITPTE call for incorporating spatial price dependence in existing 'traditional' estimation models, i.e. 'spatial' models.

Estimating 'spatial' import tariff pass-through models is increasingly becoming relevant given the growing discipline of spatial econometrics modelling. For instance, there are a few intra-trade studies that focused on determining the existence or non-existence of spatial dependence of agriculture product prices between different markets (c.f. Deodhar et al., 2007; Ghosh, 2011; Beag and Singla, 2014). Tapping into this literature, this study delves into the currently missing connection between the spatial distribution of domestic goods prices and the ITPTE, at the global level.

The analysis in this study focuses on a low-income country-Zimbabwe as a case study since import tariff pass-through studies are scarce for sub-Saharan Africa countries. In addition, Zimbabwe went through some unique characteristics which makes this study more interesting. In the recent past (2009-2014) Zimbabwe experienced hyperinflation and adopted a unique economic system of multiple currencies and a fiscal cash budget (ZEPARU, 2012; RBZ, 2014; CZI, 2013). The multiple currencies limited the country's influence on exchange rates. It could only affect trade flows by adjusting import tariff rates and non-tariffs barriers. Hence, analyzing

[3] This is whereby a regression model leaves out relevant variables. Therefore, the model will attribute the effect of the missing variables to the estimates of the included variables, which compromises precision of the latter estimates.

the ITPTE for Zimbabwe during the specified period is crucial for understanding whether import tariffs partly contributed to concurrent price-related economic hardships faced by many Zimbabweans, with implications for pro-welfare policies. Moreover, the number of countries that are adopting other countries' currencies is growing, e.g. Ecuador, El Salvador, Panama, Liberia, Guatemala and Zimbabwe (Minda, 2005). A further increase in such countries is also anticipated with growing pressure towards currency unions. Hence, this study will also serve to inform such countries of the likely effects of import tariffs on domestic goods prices.

Specifically, this study aims to incorporate the distribution of domestic goods prices across Zimbabwean regions (districts) in analysing the country's ITPTE. The study has two objectives. First, is to analyse whether there is spatial dependence in domestic goods prices across Zimbabwean regions (districts) using micro-data for the period 2009-2014. Second, is to investigate whether a failure to control for the spatial distribution of domestic goods prices results in over- or under-estimation of the ITPTE effect. Prices survey data from the Zimbabwe Statistical Agency (Zimstat), import tariff rates from Zimbabwe Revenue Authority (ZIMRA) and Zimbabwe shapefiles are employed for the analysis. To achieve the first objective, the study uses spatial maps, spatial regression models, local and global Moran's I, Geary's C, and Getis and Ord's G indices. The second objective is realized by comparing estimates of the ITPTE from the 'traditional' and the 'spatial' regression model that accounts for the distribution of domestic goods prices.

This study estimated ITPTE at a regional level factoring the regional price distribution. Various spatial econometrics model used agree that there is positive spatial dependence of domestic goods' prices. Hence a new ITPTE model which account for the price distribution was used to estimate the ITPTE. Firstly, the study found a positive and significant portion of import tariffs being passed on to domestic goods prices in Zimbabwe. Secondly, the study compared the proposed new ITPTE estimation model to the traditional model. The traditional ITPTE model was found to highly overestimate the import tariffs pass-through effect. Such findings show the implication of price distribution. Thus, future ITPTE studies are highly recommended to factor the price distribution regional prices in the estimations. Including price distribution and doing the ITPTE at regional level will not only provide precise regression estimates but it will also help developing disaggregate regional-specific policy intervening as opposed to blank policy interventions. There is no doubt that such developments will improve policy effectiveness in handing issues like wealth and income inequality, industrialisatin, inflation, and regional development.

The rest of the study is structured as follows; sections 1.0-1.1 provide some background for the study. Section 2-3 presents the theoretical literature review. Methodology and data are discussed in sections 4-5. Findings of the study are analyzed in sections 6 while section 7 concludes.

1.1 Spatial price distribution in Zimbabwe

The declining economic performance of the Manufacturing sector has brought about disproportionate benefits and cost of import tariffs to households in diverse regions (RBZ, 2009). In 2008 subsequent to the hyperinflation that was linked to other economic challenges in Zimbabwe, the economy started depending on imported products (CZI, 2010). Such an atmosphere meant dissimilar regional goods prices in the face of import tariffs. Following the gravity model, McCulloch et al. (2001) and Winters (2000c) regions that are situated closer to the country's major borders such as Beitbridge and Matabeleland South could have incurred lower goods prices compared to those far from the borders, due to low transport cost for instance. This makes it important to study the import tariffs pass-through effect in Zimbabwe accounting for price differences across the country's regions. Import tariffs were a significant source of revenue for the country post –the hyperinflation period, hence it is crucial to delve into their potential effect on domestic goods prices with implications for household welfare.

There are four possible reasons why goods prices in Zimbabwe's districts could be highly interdependent. Firstly, Zimbabwe is relatively small in geographical size (covers 390 352 km^2 with roughly 14 million people as of 2014[4]) and its districts are close to each other which means what happens in one district can be quickly communicated across districts. Secondly, most Zimbabwean markets are highly centralized. Some good examples are the markets for grain-maize, fresh vegetables, cotton, and tobacco[5]. Tobacco and cotton produced from different districts find their way to Harare, the capital city, where the central market and auctions are located. This would mean a strong cotton price dependence between Harare and the major cotton-producing districts namely, Gokwe South, Mbire, Chiredzi, Kadoma and Mwenezi district (Cotton Company of Zimbabwe Limited, 2018[6]; Agriculture Marketing Authority, 2017[7]). The price dependence would be much stronger among the districts which are closer to

[4] https://data.worldbank.org/country/zimbabwe
[5] These goods are included in some product groups later used in the analysis, the implication of the above market is that they point to greater likelihood of price dependence across districts.
[6] http://www.thecottoncompany.com/
[7] https://www.ama.co.zw/

each other and would be expected to fade away as the distance between the districts grows. The same goes with fresh vegetables from different districts which also find their way to Harare-Mbare where the biggest vegetable market is located.

Thirdly, during the period 2009-2014, the local industrial capacity was low such that most goods that were consumed in Zimbabwe were imported. South Africa was Zimbabwe's biggest trading partner at the time, supplying most of the country's imports. Prices of these goods across Zimbabwe's districts were bound to be influenced by economic conditions in South Africa. Hypothetically, prices of similar imported products are expected to be correlated across districts, factoring in distribution costs like transport, packaging, and regulation factors.

Fourthly, the hyperinflationary period of 2006-2008 created a strong interconnection of markets in Zimbabwe. Prices of goods would change more rapidly, and retailers had to keep up with price changes as they feared failure to restock their shops. Most retailers across the country depended on black markets for foreign exchange to import the goods. The black markets in different cities were all connected to what was happening in the capital city -Harare. A change of the exchange rate in Harare would be quickly communicated to other cities as they tried to keep up. This market chain arguably had some time lags, but it shows the strong connectedness of markets in Zimbabwe.

Before determining the spatial distribution of prices and the spatial effects of import tariffs, we note that the country's historical spatial settlement patterns, rainfall patterns and agriculture regions already indicate price differences across regions. Prior to independence in 1980, European White settlers had relocated black Zimbabweans to the country's less fertile and semi-arid regions. Zimbabwe is generally divided into 5 Natural Farming Regions (NFR) as shown in Table 1-1 below.

Table 1-1: Natural Farming Regions in Zimbabwe

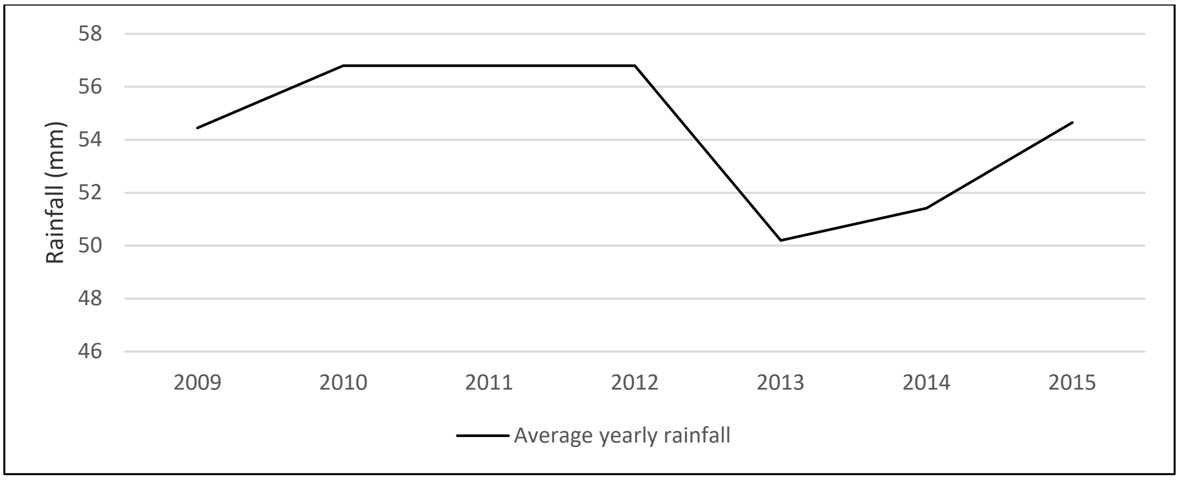
Natural Farming Region (NRF)	Province covered	Characteristics
1	Manicaland	1050mm or more rainfall per annum, relatively low temperature
2	Mashonaland East, Harare, Mashonaland Central	700-1050 mm rainfall per annum
3	Mashonaland West, Midland	500-700mm rainfall per annum, relatively high temperatures, subjective seasonal droughts
4	Matebeleland North, Matabeleland South	450-600mm rainfall per annum and subject to frequent seasonal droughts
5	Masvingo	less than 500mm rainfall per annum poorer soil

Source: Dube (2008)

White settlers forced the majority-black Zimbabweans to move from NFR 1 and 2 into NFR 3, 4 and 5 which have high temperatures and receive lower rainfall (Dube, 2008). Provinces in NFR 1 and 2 also happened to have better roads and railway infrastructure and they also house most of the country's agriculture industries (Dube et al., 2013). Though the 1980 independence tried to address this disparity, the effects are still being felt. For instance, prices of agriculture products are expected to be higher in NFR 3, 4 and 5. However, this is subject to a good rainfall season and good economic performance. Recently the country has not been receiving enough rainfall as shown in Figure 1-1 above.

Over the 2009-2014 period, the country received a yearly average maximum rainfall of 56.7 millimetres between 2010 and 2012, and a minimum yearly average rainfall of 50 millimetres in 2013. Its economic performance had also been subdued, given an average GDP growth rate of 6.3 percent yet the country was recovering from a negative 17.7 GDP growth rate which was recorded in 2008[8], resulting in dependence on imports. This benefitted more regions that are located closer to the country's major trading partners like South Africa, Botswana, and Namibia. This situation partly implies that goods prices were expected to be lower in Matebeleland North, Matebeleland South and Masvingo provinces.

Figure 1-1: Average Yearly Rainfall



Source: World Bank Climate Data Portal (2018)

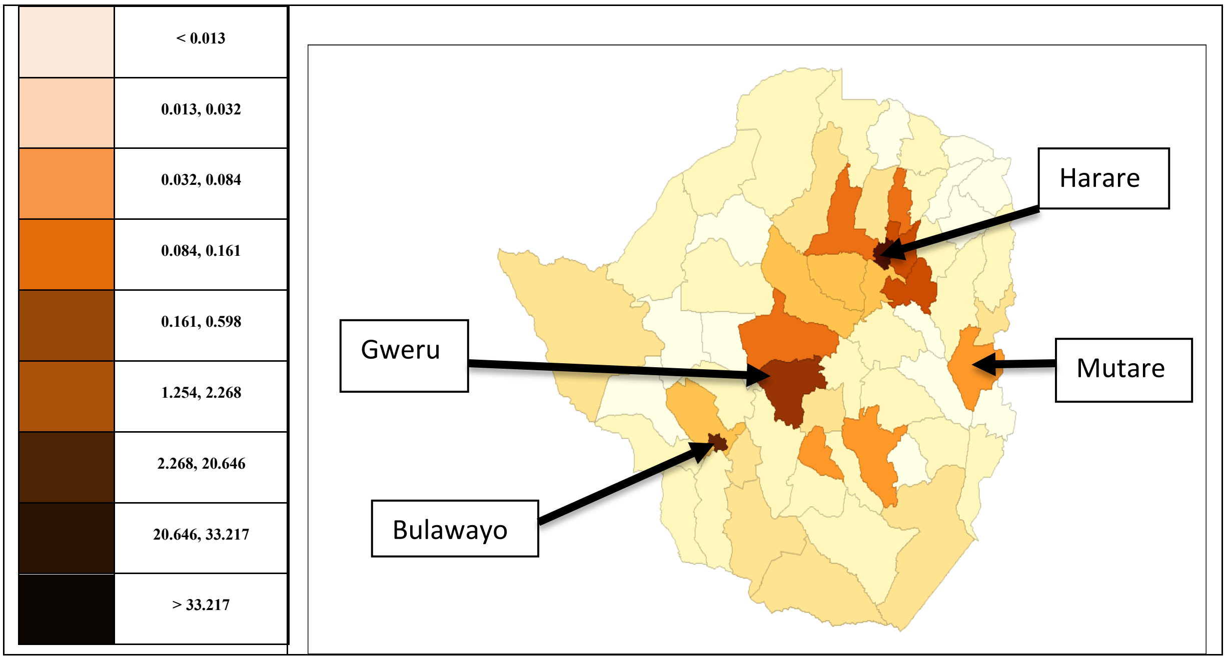
Another indicator that can also show the prior spatial difference of prices in Zimbabwe is the level of economic activities across different districts. Night light has been used as a proxy for measuring economic growth or the level of economic activities (Ebener et al., 2005; Doll

[8] https://data.worldbank.org/country/zimbabwe

et al., 2009 and Xi et al., 2010). In Figure 1-2 below we present the spatial map of night light in Zimbabwe for the year 2012. The data used in the map were taken from QGIS Rasta files.

Figure 1-2 shows night light distribution in Zimbabwe, a proxy for economic activities. It reveals some differences in levels of economic activities across districts in Zimbabwe. In Figure 1-2, the darker the colour the more the night light intensity, which implies higher economic activity. Districts in Harare and Bulawayo have the highest levels of economic activities followed by other districts like Mutare, Gweru, Zvishavane and Marondera among others. There are industrial hubs or mining activities in these districts with high night light intensity. A district located closer to an industrial hub is highly likely to enjoy lower prices of the industrial hub's output. Following the price gravity model, price varies with distance (Campa and Goldberg, 2011). Therefore, districts far away from the industrial hub are bound to have higher prices. This map thus provides prior information on how prices in Zimbabwe are likely to be distributed.

Figure 1-2: Night Light Map of Zimbabwe for the Year 2012



Source: other computations using data from arcgis.com

2 Theory of import tariffs pass through to domestic goods prices

The theoretical model of import tariffs-pass through to domestic goods prices highly borrows from the law of one price (LOP) which encompasses the works of Engel and Rogers (1996); Ceglowski (2004) and Goldberg (1996), among others. The LOP states that in a well-functioning economy, the price of similar goods should be the same in different regions, subject to transport cost. If at one point the price of say bread is \$1 in region A and \$2 in region B then, traders would arbitrage by buying bread from region A and selling it in region B. Over time prices in both markets will change in response to the forces of supply and demand such that the disparities will disappear as prices conform to the LOP (Rogoff et al., 2001).

Evidence has shown some inconsistencies in prices meeting the LOP. Some studies have pointed to the movement towards the LOP being currently slower compared to the situation in the fourteenth and thirteenth centuries (Maurice and Rogoff, 2000; Alan, 2000). The main drivers of the failure of prices to conform to the LOP have been cited as growing domestic nominal price rigidities, high nominal exchange rate volatilities, market segmentation, capital controls, coordinated financial regulation and coordination in trade policies (Rogoff et al., 2001).

Other evidence for the failure of the LOP is that goods have different attributes even when they are similar and that consumers have imperfect information about prices in different places (Ceglowski, 2004). This study acknowledges the growing evidence of the failure of the LOP and accepts that prices are different across regions even after accounting for transport cost and exchange rate variation. Against this backdrop, we assume that the consumer basket comprises imported and domestically produced goods. Betts and Devereux (2000) noted that imported goods prices are temporarily rigid if markets block the transmission of import tariffs to domestic goods prices. Obstfeld and Rogoff (2001) also pointed out that the import tariffs pass through to domestic goods prices is influenced by whether prices are set in producer or local currency. Prices are relatively sticky downwards in the producer's currency. Thus, the production and distribution channels affect the pass-through mostly if intermediate inputs are imported. These models consider all the economic agents in optimization behaviour to explain the effects of import tariffs on domestic goods prices. This study focuses on the price function and acknowledges that the price-setting dynamics affect the import tariffs pass-through, and that the average unit price of goods is a function of domestic and imported goods prices.

3 Theoretical framework - domestic price dependence and import tariff pass-through

The theoretical framework adopted for this study closely follows Engel and Rogers (1996). We hypothesis a mark-up over marginal cost and a Cobb-Douglas production function. Thus, the average unit price of good 1 in district j, P_{1j} can be represented in the form:

$$P_{1j} = \mu_{1j}(P^D)^\gamma \left(P_{1j}^I\right)^{1-\gamma} \text{...........[1.1]}$$

where μ_{1j} is the mark-up over marginal cost of product *1* in district *j*, P^D captures the price of domestically sourced intermediate input, P^I is the price of imported intermediate input and $\gamma < 1$ is the substitution effect between imported and domestically sourced inputs. If $\gamma = 1$ P_{1j} will only be influenced by domestic inputs' price, and by imported inputs' price only when $\gamma = 0$. Instead of these extreme cases, we assume P_{1j} to depend on both domestic and imported inputs' prices. Furthermore, we assume that the price of imported goods P_{1j}^I is made up of import tariffs and other distribution constraint variables (*X)* which include district *j*'s distance from the border, money supply, exchange rate, distance from industrial hubs, inter alia. Hypothetically, the further is district *j* from the border the higher will be the distribution costs of the imported inputs, which feeds into a higher final price. Assuming the quantity theory of money holds, an increase in money supply will affect P_{1j}^I as per the marginal propensity to import. Importing a good also involves the exchange rate, its appreciation or depreciation alters the import price. Thus P_{1j}^I will be expressed as:

$$P_{1j}^I = P_1^B(1 + t_1) + X \text{.......... [1.2]}$$

where P_1^B is the border price of imported inputs before the addition of import tariffs, *t* is the ad valorem import tariffs rate at a given time, *X* [9]is a vector of control variables mentioned above. Due to possible spatial autocorrelation of goods prices ρP_{1k}^I is added to equation 1.2. Where ρ captures the correlation between the import price of good 1 in district *j* and district *k* i.e. P_{1j}^I and P_{1k}^I. This gives:

$$P_{1j}^I = P_1^B(1 + t_1) + \rho P_{1k}^I + X \text{......[1.3]}$$

When P_{1j}^I is independent from P_{1k}^I, it implies an absence of spatial price autocorrelation, i.e. a random price distribution. Then $\rho = 0$ and we revert to equation 1.2. If $\rho \neq 0$ it denotes a spatial correlation between P_{1j}^I and P_{1k}^I; prices in the two districts depend on each other. Noteworthy in 1.3 is that P_{ik}^I is also a function of import tariffs and prices from other districts such that for simplicity P_{ik}^I can be expressed as:

$$P_{1k}^I = P_1^B(1 + t_1) + X + \rho P_{1l}^I \text{......[1.4]}$$

If we substitute 1.4 into 1.3 we get

$$P_{ij}^I = P_1^B(1 + t) + X + \rho P_1^B(1 + t) + \rho X + \rho^2 P_{1l}^I \text{...[1.5]}$$

[9] It should be noted that there is a thin line between imported intermediate and imported final goods, someone's intermediate input is another one's final goods thus X remain valid in equation 1.2.

Notably P_{1l}^{I} also depends on import tariffs and prices from other districts. Without loss of generality, we assume that there are three districts only, i.e. *j, k* and *l*. However, in reality, these districts can go even up to 100. Transforming 1.1 into logarithms, substituting 1.5 and differentiating with respect to import tariffs *t* we get;

$$\frac{\partial logP_{1j}}{\partial t} = \frac{(1-\gamma)P_1^B(1+\rho)}{P_1^B(1+t)(1+\rho)+X(1+\rho)+\rho^2 P_{1l}^I}\frac{\partial P_{1l}^I}{\partial t} \ldots\ldots[1.6^{10}]$$

$$\text{Given that } \gamma < 1\text{, then } \frac{\partial logP_{1j}}{\partial t} > 0 \ldots\ldots[1.7]$$

Equation 1.7 implies a positive relationship between import tariff changes and domestic goods prices, which can be less or greater than 1 depending on the other components of 1.6. That is the post-tariff percentage change in the domestic price of good 1 can be less than the percentage change in import tariffs (incomplete pass-through), or 100 percent of changes in import tariffs can be transmitted to goods prices (complete pass-through).

When $\rho = 0$ that is spatial price randomness, then

$$\frac{\partial logP_{1j}}{\partial t} = \frac{(1-\gamma)P_1^B}{P_1^B(1+t)+X} \ldots\ldots[1.8]$$

Equations 1.6 (positive spatial dependence) and 1.8 (spatial randomness) show that the effect of import tariffs changes on domestic goods prices depends on the nature of spatial price distribution. There could also be a negative spatial dependence where that prices in proximate districts move in opposite directions, thus ρ in 1.6 will have a negative sign. The aspect of the spatial weights matrix will be introduced in the next section to capture the closeness of the districts to each other, i.e. price network effect. As such, the ITPTE could be influenced by the underlying characterization of the domestic goods price distribution across regions. It is also noteworthy that the import tariff effect can differ across regions within a country which accentuates the importance of regional variables in this framework.

It can also be inferred from equation 1.6 that if ρ and X increase independently then $\frac{\partial logP_{1j}}{\partial t}$ which is the import tariffs pass-through will decrease, ceteris paribus. Thus, high levels of spatial dependence and distribution constraints are associated with low import tariffs pass-through. A further inference is that as the imported and domestic input substitution effect γ decreases, the import tariffs pass-through effect increases. This implies that it becomes difficult

[10] $logP_{1j} = log\mu_{ij} + \gamma logP^D + (1-\gamma)logP_{1j}^I$…….1.1.1
Substituting 3.5 into 3.1.1 $logP_{1j} = log\mu_{ij} + \gamma logP^D + (1-\gamma)\log[P_1^B(1+t) + X + \rho P_1^B(1+t) + \rho X + \rho^2 P_{1l}^I]$… 1.5.1
Differentiation 1.5.1 with respect to import tariff t $\frac{\partial logP_{1j}}{\partial t} = \frac{(1-\gamma)P_1^B(1+\rho)}{P_1^B(1+t)(1+\rho)+X(1+\rho)+\rho^2 P_{1l}^I}\frac{\partial P_{1l}^I}{\partial t}$…….1.6

to pass-through a larger share of import tariffs changes to domestic goods prices when a greater portion of imported inputs are used to produce final goods.

4 Methodology: Determining the spatial distribution of prices

To determine the nature of the spatial distribution of domestic goods prices across Zimbabwean districts, the study uses spatial maps, Moran's I (Moran, 1948), Geary's C (Geary, 1954), Getis and Ord's G (Getis and Ord, 1992) indices and spatial regression methods. Tests based on these indices are carried out at global and local levels. The global, I, G and C indices present the overall degree of dependence between spatially close regions in a study area (A) with respect to a numeric variable x (Pisati, 2012). Their local versions present for each location i in area A the degree of similarity between that region and its neighbouring regions with respect to x. Thus, global indices capture a general tendency towards clustering, while local indices detect specific spatial clusters (Pisati, 2012; Pfeiffer et al., 2008). Consequently, results for local indices may differ from those of global indices when spatial dependence is clustered among a few districts. The following formal discussion of these indices closely follows Viton (2010) and Technical Stata Bulletin (2001).

The global Moran's I use the z-score to test the null-hypothesis of no spatial autocorrelation against the alternative of spatial autocorrelation. It is defined for a variable of interest x as:

$$I = \frac{R}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\sum_i (x_i - \bar{x})^2} \text{..... [1.10]}$$

where R is the number of locations in the analysis. w_{ij} are elements of the spatial weights matrix W for location pair (i, j). x_i is the value of x at location i. $\overline{x}$ is the mean of x. If I is larger (smaller) than its expected value, then the distribution of x has a positive (negative) spatial dependence. This implies that values of x in surrounding districts tend to be similar (dissimilar). The global Moran's I treat districts that are 50 and 500 kilometres away from the same as if they are in the neighbourhood. This concept slightly contradicts Tobler's (1970) first law of geography - everything is related to everything else but closer things are more related than distant things, which motivates for the local measure.

Unlike Moran's I, the global Geary's C (Geary, 1954) index is sensitive to local autocorrelation. This is formally defined as:

$$C = \frac{R-1}{\sum_i \sum_j w_{ij}} \frac{\sum_i \sum_j w_{ij}(x - \bar{x})^2}{\sum_i (x_i - \bar{x})^2} \text{.........[1.11]}$$

Under the null hypothesis of no global spatial autocorrelation, the expected value of c equals 1. If c is larger (smaller) than 1 then the x has a negative (positive) spatial dependence (Pisati, 2012).

Getis and Ord's G statistic is specified as:

$$G = \frac{\sum_{i \neq j} w_{ij} x_i x_j}{\sum_{i \neq j} x_i x_j} \text{..........[1.12]}$$

If G is larger (smaller) than its expected value, then the overall distribution of x has a positive spatial dependence with a prevalence of high (low)-valued clusters (Getis and Ord, 1992).

As for the local I, G and C indices, they are derived from the global indices and share their basic properties (Pisati, 2012; Pfeiffer et al., 2008).

Spatial maps of price distribution among Zimbabwean districts are drawn using shapefiles from ArcGIS and the GeoDa software program. The shapefiles have 60 districts covering 10 provinces, they also provide the districts' latitude and longitude coordinates. Goods prices at the district level are sourced from Zimstat. A visual analysis of the maps gives an indication of the nature of price distribution across the districts.

The study also runs five types of spatial regression models that are consistent with panel data. These models are:

1. Spatial Autoregressive Model (SAR) with a lagged dependent variable, which can be formally specified as:

   $$P_t = \alpha_{ln} + \rho W P_t + X_t \beta + \mu_t \text{........ [1.13]}$$

   For a panel dataset in which n units (districts) are observed for exactly T periods, P_t is an $n \times 1$ column vector of log of prices and ι_n is an $n \times 1$ vector of ones associated with the constant term parameter α. Given that the dataset at use has time and individual effects, model testing is applied to exhibit whether the appropriate model is a fixed effect or a random effect. W is an $n \times n$ spatial weights matrix. Each element (j, k) of W denoted by $w_{j,k}$ shows the degree of spatial proximity of district j and k. Thus, W controls for the nature of spatial price distribution encountered in this data; it captures the network and interactions of pricing agents in districts j and k (Anselin, 2002; Pisati 2012). X_t is an $n \times k$ matrix of log regressors associated with parameters β contained in a $k \times 1$ vector and $\mu_t = (\mu_i, \dots, \mu_n)^T$ is a vector of independently and identically distributed disturbance terms (zero mean and variance σ^2). ρ is the spatial autoregressive parameter. If ρ is positive (negative) and statistically significant it implies that there is positive (negative) spatial price autocorrelation and an insignificant ρ implies random price distribution.

2. To capture the possibility that some regressors in X_t are spatially autocorrelated, for instance, temperature and rainfall patterns tend to be similar in proximate districts, the study employs the Spatial Durbin Model (SDM). The SDM is a generalised SAR model which includes spatially weighted independent variables as explanatory variables. The model is specified as:

$$P_t = \alpha_{ln} + \rho W P_t + x_t \beta + \emptyset \gamma \eta_t + \mu_t \text{ …... [1.14]}$$

   where η_t is an $n \times 1$ matrix of log of regressors which depict spatial dependence, γ is an $n \times n$ spatial weights matrix for the spatially lagged regressors, the other variables are as explained in equation 1.13.
3. The Spatial Autoregressive Model with Spatially Autocorrelated Errors (SAC) - this model combines the SAR with a spatial autoregressive error. It is specified as:

$$P_t = \alpha_{ln} + \rho W P_t + x_t \beta + V_t \text{…….[1.15]}$$

   where $V_t = \lambda E V_t + \mu_t$. E is the $n \times n$ spatial weights matrix for idiosyncratic error terms.
4. Spatial Error Model (SEM) - this model can be treated as a special case of both the SAR and SDM. It focuses on spatial autocorrelation in the error term, thus it treats spatial dependence as a nuisance (Pisati, 2012). The model is specified as:

$$P_t = \alpha_{ln} + x_t \beta + \mu_t \text{……..[1.16]}$$

$$\text{where } \mu_t = \lambda E v_t + \varepsilon_t \text{………[1.17]}$$

5. Generalised Spatial random-effect model (GSPRE), which is represented as:

$$P_{1kt} = \alpha + x_t \beta + \mu_t \text{……..[1.18]}$$

$$\text{where } \mu_t = \lambda E v_t + \varepsilon_t \text{……[1.19]}$$

$$\text{and } \alpha = \theta W \alpha + \eta \text{……..[1.20]}$$

The GSPRE assumes panel effects α are spatially correlated, η and ε_t are independently normally distributed errors so that the model is necessarily a random-effects model.

Post-estimation of models 1-5, the Likelihood Ratio test (LR test), Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) are used to determine the most appropriate model for the study. The study employs STATA version 14 statistical package to run the above regression models.

Notably, there are two approaches to constructing the spatial weights matrix; contiguity and based on distance. The contiguity approach creates the matrices based on spatial units which share common borders. Under this approach, there is the Rook criterion which uses common borders, the Bishop criterion which uses common vertex and the Queen criterion which uses either common borders or common vertex. For weights matrices based on distance, there are the Euclidean matrix, Manhattan matrix and the Minkowski matrix (Anselin, 1988). This study will consider the different types of spatial weights matrices. Appendix 1-A1 provides a description of variables used in the analysis as well as apriori expected relationships between the covariate and dependent variables.

4.1 Incorporating price distribution into the import tariffs pass-through model

This study estimates two types of import tariff pass-through models 'traditional and 'spatial' and compares the results, especially the ITPTE. The 'spatial' models control for the spatial distribution of domestic goods prices while the 'traditional' models do not. The 'traditional' model used to estimate the ITPTE is presented in equation 1.21 (Liu and Tsang, 2008; Marazzi et al., 2005; Mumtaz et al., 2006; and Zubair et al., 2013).

$$\Delta logP_t = \beta_0 + \beta_1 \Delta logtar_t + \beta_2 logmon_t + \beta_3 \Delta logexc_t + \beta_4 \Delta x_t + \beta_5 y_t + \epsilon_t.. \quad [1.21]$$

where $\Delta logP_t$ is a change in the log of domestic goods prices of good *i* at time *t*, β_0 is a constant, $\Delta logtar_{1t}$ denotes a change in the log of import tariffs of good *i* at time *t* (policy consistent factor), mon_t is money supply at time *t* (policy consistent factor), exc_t is the exchange rate of the United States of American Dollar (US$) to South African rand at time *t*. Though Zimbabwe had no exchange rate during the period 2009-2014 most economic variables like inflation rate, poverty datum line were highly correlated with the US$ to South African rand exchange rate (ZEPARU, 2012). *X* are other region-specific explanatory variables at time *t*, including temperature and rainfall. *Y* includes regional specific indicator variables for rural/urban location, year and month among others. The key variable is $\Delta logtar_t$ with its coefficient β_1. This gives the percentage magnitude of changes in import tariffs that are passed on to domestic goods prices.

For the 'spatial model, a spatial weights matrix is added to equation 1.21 as in equation 1.22 (Long et al., 2016; Chen et al., 2017; Tsutsumia and Tamesuea, 2011 and Wheeler et al., 2013).

$$\Delta logP_t = \beta_0 + \beta_1 \Delta logtar_t + \beta_2 logmon_t + \beta_3 \Delta logexc_t + \beta_4 \Delta x_t + \beta_5 y_t + \beta_4 W \Delta logP_t + \epsilon_t. \quad [1.22]$$

Specifically, $\beta_4 W \Delta logP_t$ controls for the spatial distribution of domestic goods prices as per section 1.3. Equation 1.22 is a spatial lag model, however, the most appropriate spatial regression model and estimation technique will be used following results for models in section 1.1.

5 Data Source and Descriptive Statistics

The ZIMRA documents integrated customs tariffs in a handbook which is updated after every 5-10 years. Small updates or changes to the tariffs are published in the Government Gazette. This study utilises the integrated tariffs handbook as the key source of import tariffs data complemented by Government Gazette publications. Data on money supply and exchange rates are sourced from the RBZ's Monthly Economic Review (RBZ, 2009-2014). GIS Raster Files[11] were used to extract data on night light and temperature while Zimbabwe's Shape-files[12] were used to calculate distances across districts. In addition, the study utilises a nationally representative dataset from the monthly consumer goods prices surveys produced by the Zimstat, covering 60[13] districts over the period 2009-2014. Noteworthy, the shape-files do not provide sub-district demarcations for some towns and cities e.g. Harare, Bulawayo, Gweru and Mutare. Hence, this study treats them as 'composite' districts. Using Harare as an example, the Zimstat price data has prices for Harare urban, Harare rural and Epworth sub-districts (excludes Chitungwiza district). In dealing with this limitation the study proceeded by taking the average of goods prices for Harare urban, Harare rural and Epworth as the price for the Harare district. However, the extent to which this aggregation biases the study's regional price distribution analysis remains an empirical question. Chances are that bias may (may not) occur if the aggregated sub-districts have statistically dissimilar (similar) prices, although the latter is highly likely.

Products covered by the prices survey can be grouped into, Food, Non-Alcohol Beverages, Alcohol Beverages, Cloth, Footwear, Fuel, Household Textiles, Vehicle Fluids and Furniture; as shown in Table 1-2 below[14].

[11] Sourced from https://www.diva-gis.org/datadown

[12]Sourced from https://www.diva-gis.org/datadown

[13] Originally the pricing surveys had 82 districts while shape-files had 60 districts. Thus, only 60 districts could be matched from the shape-files to the price surveys. There are fewer districts in the shape files as some cities and towns were presented as one district which masks the sub-districts.

[14] Less emphasis will be place on analysing product group "other" it has only 2 products.

Table 1-2: Product groups

Product Groups	Number of Products
Food	18
Non-Alcohol Beverages	7
Alcohol beverages	9
Clothes	50
Footwear	6
Fuels	9
Household textiles	7
Vehicle fluids	3
Furniture	8
others	2

Source: Stata output using price surveys from Zimstat 2009-2014.

Table 1-3 presents summary statistics for consumer goods prices (dependent variables) in US$ at the district level. These include the overall mean, and variation between districts and within period (years) of the product prices. The overall average yearly price of food items is US$4.26, the food prices also differ across the 60 districts and within the 6 years of study as given by the different standard deviations, minimum and maximum values. A comparison of the average prices across products reveals some cross-product price differentials. For instance, Table 1-3 shows an overall mean price of US$2.24 for non-alcohol beverages, US$5.75 for cloth, US$6.97 for footwear, US$17.40 for fuel. Like the case for food, the product prices for the other goods in Table 1-3 also exhibit differences across districts and within the 6 years as shown by the standard deviation, minimum and maximum price columns. As an example, the standard deviation for non-alcohol beverages between districts (within periods) is 0.78 (0.71) while those for alcohol beverages and cloth are 0.43 (0.35) and 1.95 (1.41).

The price differentials distinguished across districts are further unpacked in Table 1-4. For brevity, Table 1-4 shows mean values for 9 product prices across 7 randomly chosen districts. In contradiction with the LOP, Table 1-4 attests to some price disparities across the districts. For instance, the average food price in Bulawayo is US$3.86; US$4.30 in Harare; US$6.24 in Mutasa. For cloth, the average price in Bulawayo is US$3.90; US$6.10 in Harare; US$9.02 in Mutare. Analogous to Figure 1-2, Table 1-4 also shows relatively low average prices in Bulawayo and Harare compared to districts such as Chimanimani, Chipinge, Makoni, among others. These regional price differences motivate our analysis of spatial price distribution. It can also be noted that furniture and fuel prices are generally high relative to other goods' prices. Hence, the study will utilize log prices in the regression analysis.

Table 1-3: Summary statistics of the product prices (2009-2014) US$

Variable		Mean	Standard deviation	Minimum	Maximum	Observations	
All Food	overall	4.256	1.059	3.093	7.505	N =	360
	between		0.873	3.994	7.595	n =	60
	within		0.624	4.256	4.456	T =	6
Non-Alcohol Beverages	overall	2.240	1.053	0.861	5.188	N =	360
	between		0.781	0.619	5.832	n =	60
	within		0.713	2.740	2.940	T =	6
Alcohol Beverages	overall	2.57	0.537	1.762	3.857	N =	360
	between		0.425	1.245	3.704	n =	60
	within		0.346	2.574	2.874	T =	6
Cloth	overall	5.75	2.39	2.140	12.153	N =	360
	between		1.953	2.032	11.136	n =	60
	within		1.407	5.746	5.976	T =	6
Footwear	overall	6.97	3.508	1.453	14.987	N =	360
	between		3.097	1.367	1.857	n =	60
	within		1.694	6.967	6.997	T =	6
Fuel	overall	17.40	12.646	1.254	46.235	N =	360
	between		12.062	1.401	44.133	n =	60
	within		4.061	17.403	17.983	T =	6
Textiles	overall	6.61	2.655	2.389	13.234	N =	360
	between		1.965	2.952	12.261	n =	60
	within		1.817	6.609	6.691	T =	6
Vehicle Fluids	overall	6.27	3.089	1.746	13.797	N =	360
	between		2.793	1.881	12.754	n =	60
	within		1.375	6.270	6.750	T =	6
Furniture	overall	338.89	50.451	132.57	457.452	N =	360
	between		28.734	134.59	433.612	n =	60
	within		41.615	338.894	339.984	T =	6
All goods	overall	29.45	4.890	0.861	457.452	N =	360
	between		3.956	0.8419	477.275	n =	60
	within		5.832	2.240	338.894	T =	6

Source: Stata output using price surveys from Zimstat 2009-2014.

Table 1-4: Average price for 8 randomly chosen districts (US$) (2009-2014)

	Bulawayo	Harare	Chimanimani	Chipinge	Makoni	Mutare	Mutasa
All Food	3.855	4.298	5.168	4.216	7.088	5.179	6.238
Non-Alcohol Beverages	2.068	3.460	4.646	4.567	3.976	3.843	4.429
Alcohol Beverages	2.276	2.434	3.514	2.496	3.479	2.452	3.392
Cloth	3.900	6.104	8.253	9.095	7.092	9.022	10.807
Footwear	4.246	7.410	10.680	9.519	12.509	10.427	12.207
Fuel	9.222	23.460	23.686	23.551	23.543	23.474	23.289
Textiles	4.618	6.717	10.987	9.826	11.817	8.734	10.514
Vehicle Fluids	3.668	8.002	11.362	9.147	9.134	10.024	11.732
Furniture	312.737	290.218	308.238	297.470	296.842	291.328	276.620
All goods	25.619	27.175	38.599	37.718	42.649	39.212	43.006

Source: Stata output using price surveys from Zimstat 2009-2014.

Table 1-5 presents descriptive statistics for selected independent variables used in the following regression analysis; import tariffs, exchange rates, money supply, temperature, and rainfall. Importantly, information on import tariffs rates was available in different types; ad valorem, specific and mixed (partly ad valorem and partly specific) import tariff rates. These were also specified for bilateral, general, and multilateral trade agreements. For this study, non-ad Valorem tariffs were converted to ad valorem, and for the different goods, an average ad valorem import tariff rate was calculated across the different trade regimes. That said, a cursory look at Table 1-5 reveals that the variables are not constant across time. For example, the overall and within standard deviations for import tariffs are 7.25 and 6.32, respectively. Notably, there is no between district variation for import tariffs, money supply and exchange rate as they are national-level variables. However, temperature and rainfall vary across districts. Using the standard deviation for temperature and rainfall we observe the overall (14.24; 134.92), between (13.49; 122.02) and within (28.16; 59.34) tendencies of dispersion. This covariate distribution across time and space allows for our multivariate analysis of regional price distribution in Zimbabwe.

Table 1-5: Descriptive statistics for covariates[15]

Variables		Mean	Standard Deviation	Minimum	Maximum	Observations	
Imports Tariffs	overall	18.37	7.25	0	100	N =	360
(ad valorem)	within		6.32	5.97	33.29	T =	6
Exchange rates	overall	8.58	1.38	6.72	11.46	N =	360
(US$/rand)	within		1.36	6.63	11.11	T =	6
Money supply	overall	2867.61	1236.82	297.63	4457.26	N =	360
(million US$)	within		1222.45	571.67	4354.17	T =	6
Temperature	overall	29.47	14.24	0.005	34.25	N =	360
(degrees Celsius)	between		13.49	29.58	30.77	n =	60
	within		28.16	16.80	33.17	T =	6
Rainfall	overall	344.86	134.92	0.007	563.63	N =	360
(mm)	between		122.02	107.27	548.48	n =	60
	within		59.34	157.45	559.39	T =	6

Source: Stata output using price surveys from Zimstat 2009-2014.

5.1 Tradable goods

The distinction between tradable and non-tradable goods is very important mostly when product prices are collected. Non-tradable goods are products that cannot be traded internationally or across countries. Such goods include services where the producers and consumers of the product in question are all located in the same country. The prices surveys provided by Zimstat are limited in that they do not separate tradable from non-tradable components of the consumer goods used in this study (Table 1-4). That both tradable and non-tradable goods are affected by import tariffs implies that it would have been more accurate to separate the import tariffs effect on these two types of goods (Corden, 1966). Feenstra (1989 and 2015) observed that prices of domestic non-tradable goods tended to increase as local producers took advantage of an increase in import tariffs to maximise profits. Given the lack of basis to disentangle tradable and non-tradeable portions of goods used in this study, the analysis proceeds on the assumption that all the goods are tradable. Appendix 1-A3 in the

[15] Summary statistics for remaining covariates are in Appendix 1-A2 in the appendix.

appendix attempts to provide the rationale. However, this assumption is likely to overstate the ITPTE, hence the reader should be aware of this limitation.

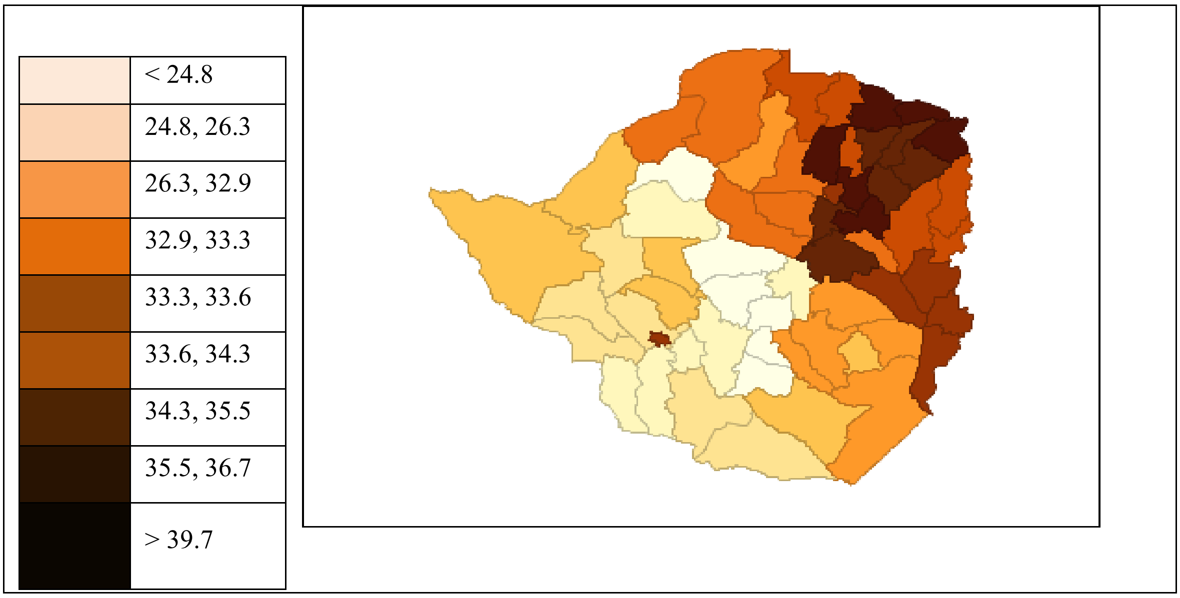
6 Presentation of results: Spatial distribution of prices

This section discusses results for price distribution in Zimbabwe. Spatial maps are discussed first followed respectively by I, C and G tests of spatial autocorrelation and spatial regression models.

Spatial maps for price distribution in Zimbabwe

Figure 1-3 presents a spatial map for the average price of all goods across 60 districts in Zimbabwe for the period 2009-2014.

Figure 1-3: Spatial Map of Price Distribution in Zimbabwe for the period 2009-2014

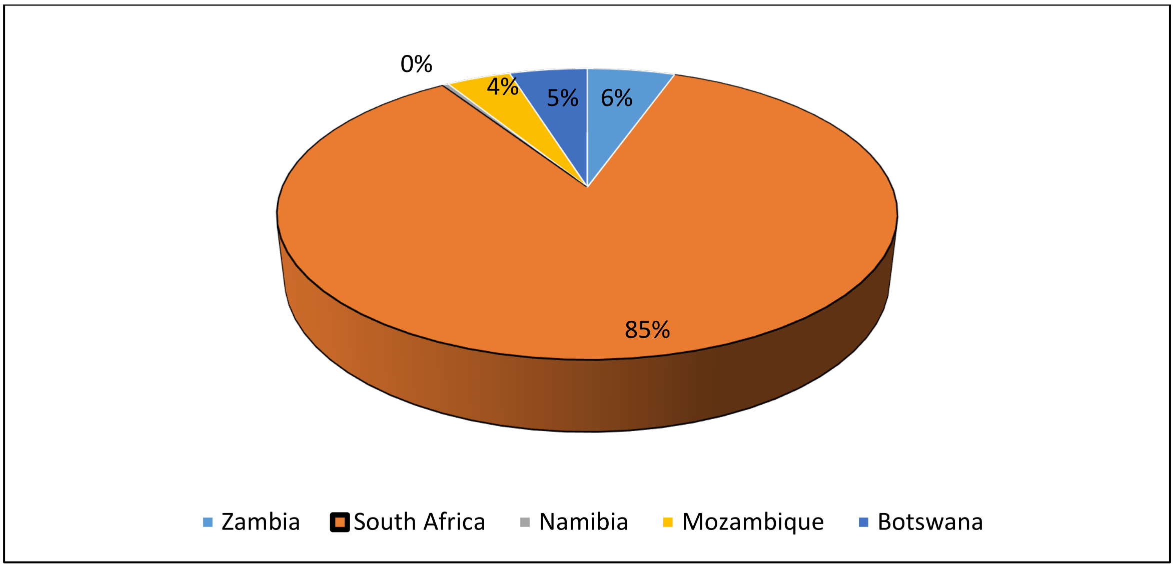


Source: Compilation in GeoDa software based on Zimstat data for 2009-2014.

In Figure 1-3, the darker the colour the higher the average goods price, the map's key shows the district average prices in US$. Prices are relatively lower in districts to the western and south-west sides of Zimbabwe, while they are relatively higher in north-east districts. To the eastern side of the country, there is Mashonaland Central, Mashonaland East and Manicaland provinces. The cities in these provinces are Harare, Bindura, Marondera, and Mutare. These cities are closer to the Mozambican border, but they are far away from the Beitbridge border and it seems as if they are not benefiting much from that. The eastern side of the country is rich in agriculture and the region is also an industrial hub with industries located in Harare and Mutare (Confederation of Zimbabwe Industry, 2014). However, these characteristics seem not to help in keeping prices lower.

Western and south-west parts of Zimbabwe house Matebeleland North, Matebeleland South and Masvingo provinces. Cities in these provinces are Beitbridge, Masvingo and Victoria Falls. These provinces do not receive good rainfall (Dube, 2008). They have dry and less fertile land for agriculture yet enjoy relatively lower prices. Most industries in western and south-west parts of Zimbabwe relocated to the capital city (Harare) following the economic crisis between 2000 and 2008 (Dube et al., 2013). These provinces are also relatively closer to the major country borders which are Beitbridge, Plumtree, Pandamatenga, Kazungula and Chirundu border posts. These borders are between Zimbabwe and South Africa as well as Botswana. Figure 1-4 shows the share of goods imported from five countries surrounding Zimbabwe for the period 2009-2014; Botswana, Mozambique, Namibia, South Africa and Zambia. The pie chart shows that Zimbabwe imported much from South Africa (85 percent) and Botswana (6 percent). This helps to explain why provinces in western and south-western parts of Zimbabwe have relatively lower prices.

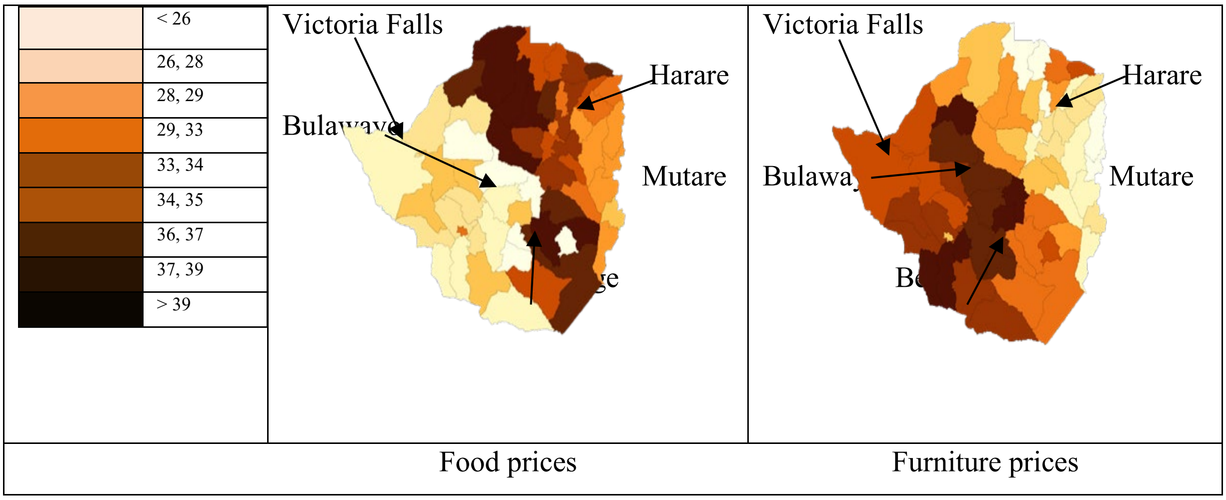
Figure 1-4: Share of Imports among 5 Countries surrounding Zimbabwe



Source: Computation. Using data from WITS: https://wits.worldbank.org.

Looking at the same map but at the product level, reveals some regional price differentials, see Figure 1-5. This shows the spatial distribution of food and furniture prices, used as an example of spatial price differences across commodities. The spatial distribution of food prices is similar to that for the overall price as shown in Figure 1-3, while that for furniture prices are evidently different from that for food. This shows some cross-commodity dissimilarity in price distribution across regions. The spatial distribution of furniture prices seems to be highly influenced by vibrant furniture industries in the eastern side of Zimbabwe.

Figure 1-5: Comparison of Food and Furniture Prices for the period 2009-2014

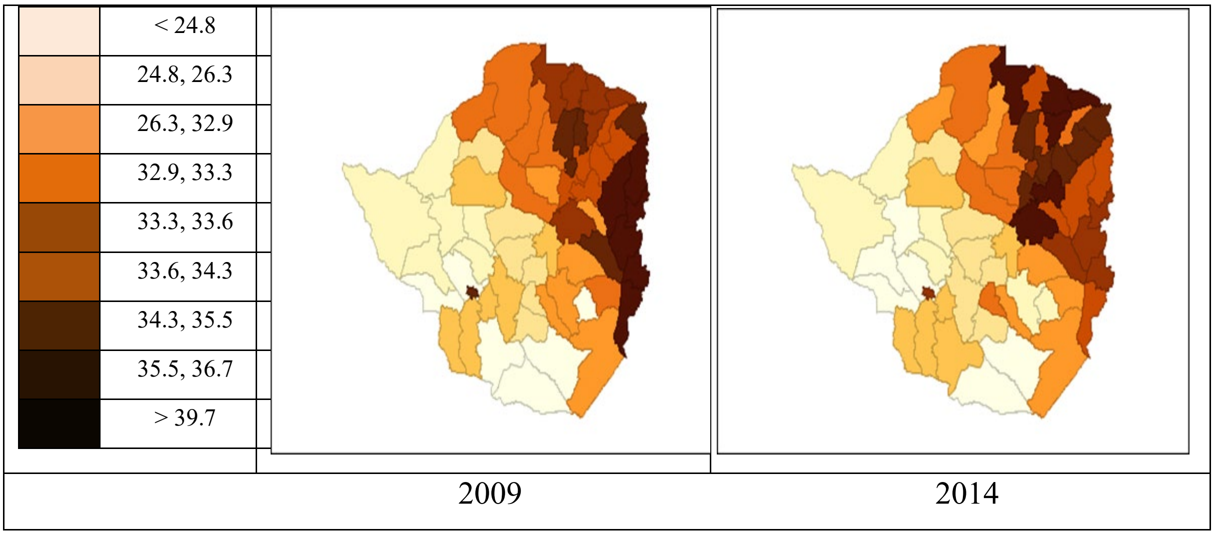


Source: Compilation in GeoDa software based on Zimstat data for 2009-2014.

Zimbabwe's eastern highlands are endowed with multiple tree plantations and furniture industries which makes the furniture industrial hub (Dube et al., 2013). Further analysis also shows that Manicaland province was the least affected by the 2000-2003 land reform programme as it had a low land take-up rate of 42 percent compared to the national average of 66 percent (Utete, 2003). Given the long-life cycle of tree plantation compared to maize and other small grains, at a time when the average rainfall pattern was erratic, it made sense for the furniture industry to continue striving while other agricultural food products were repeatedly being imported from neighbouring countries. Hence furniture prices were lower in districts located in the eastern parts of Zimbabwe. More maps at the product level are shown in Appendix 1-A4 in the appendix. However, the major lesson from these maps is that the spatial distribution of prices is different across products though some products show some similarities.

A closer analysis of the yearly maps also shows that the spatial distribution of the prices of the products varies across years. Figure 1-6 shows the spatial distribution of the average goods price for 2009 and 2014. Though there are some similarities, we can also observe slight distributional differences. For instance, districts in Manicaland province experienced higher prices in 2009 compared to 2014. This change is partly attributed to the influx of second-hand clothes from Mozambique, socioeconomic and political reasons, among others (Confederation of Zimbabwe Industry, 2013). However, districts to the west of Zimbabwe continued to experience relatively low prices in both 2009 and 2014. This might be driven by the continued importation of products from South Africa and Botswana over the period under study (African Development Bank, 2013). Taken together these maps indicate some cases where districts with low (high) prices are surrounded by districts with low (high) prices. This hints at some degree of price dependence across districts in Zimbabwe.

Figure 1-6: Comparison of Spatial Distribution across years



Source: Compilation in GeoDa software based on Zimstat data for 2009-2014.

Moran's I, Geary's C and Getis & Ord's G tests of spatial dependence

Cressie and Chan (1981) highlighted that a map can be misleading in determining spatial dependence or randomness. Hence, we continue to discuss findings for global I, C and G tests of spatial dependence presented in Table 1-6. The Moran's I test the null hypothesis of random price distribution against the alternative hypothesis of spatial dependence (Viton, 2010).

Table 1-6 Panel A shows that I indices for all product groups are greater than their expected values. An example is the case for all goods combined (textiles) where the I-statistic of 0.207 (0.379) is greater than the expected value of -0.003. The p-values are significant for all the products at the 5 percent significant value. Thus, all products exhibit a positive global spatial price dependence. Panels B and C show results for Geary' C and Getis and Ord's G, respectively. C indices for all products are less than 1, while G indices are all greater than the expectations values. This reinforces the finding of a general tendency towards positive price dependence across Zimbabwean districts that have been uncovered under Moran's I.

Table 1-6: Global I, C and G-Test statistics-domestic goods prices

	Panel A: Moran's I				
Variables	I	E(I)	Sd (I)	z	p-value*
All goods	0.207	-0.003	0.015	14.171	0.000
Furniture	0.090	-0.003	0.015	6.291	0.000
Vehicle fluids	0.628	-0.003	0.015	42.417	0.000
Textiles	0.379	-0.003	0.015	25.661	0.000
Fuels	0.616	-0.003	0.015	41.589	0.000
Footwear	0.456	-0.003	0.015	30.904	0.000
Cloth	0.534	-0.003	0.015	36.134	0.000
Alcohol beverages	0.391	-0.003	0.015	26.493	0.000
Non-Alcohol beverage	0.250	-0.003	0.015	17.047	0.000
Food	0.489	-0.003	0.015	33.190	0.000
	Panel B: Geary's C				
Variables	C	E(c)	Sd (c)	z	p-value*
All goods combined	0.839	1.000	0.037	-4.316	0.000
Furniture	0.873	1.000	0.060	-2.100	0.018
Vehicle fluids	0.408	1.000	0.022	-26.431	0.000
Textiles	0.689	1.000	0.027	-11.726	0.000
Fuels	0.422	1.000	0.023	-25.087	0.000
Footwear	0.573	1.000	0.027	-15.767	0.000
Cloth	0.592	1.000	0.031	-13.366	0.000
Alcohol beverages	0.733	1.000	0.029	-9.152	0.000
Non-Alcohol beverage	0.742	1.000	0.035	-7.318	0.000
Food	0.738	1.000	0.039	-6.716	0.000
	Panel C:Getis & Ord's G				
Variables	G	E(G)	sd(G)	z	p-value*
All goods	0.066	0.064	0.000	3.290	0.001
Furniture	0.065	0.064	0.000	0.320	0.013
Vehicle fluids	0.080	0.064	0.001	10.857	0.000
Textiles	0.072	0.064	0.001	6.900	0.000
Fuels	0.093	0.064	0.002	13.102	0.000
Footwear	0.075	0.064	0.002	7.014	0.000
Cloth	0.075	0.064	0.001	9.232	0.000
Alcohol beverages	0.068	0.064	0.001	6.010	0.000
Non-Alcohol beverage	0.070	0.064	0.001	4.146	0.000
Food	0.071	0.064	0.001	9.409	0.000

Source: Author’s Stata output based on Zimstat data for 2009-2014.

Results for local I, C and G indices for all goods combined for some districts are presented in Appendix 1-A5.A to 1–A5.C. Regions labelled L-L and H-H (H-L and L-H) represent positive (negative) spatial dependence. The results attest to local pockets of positive spatial price dependence in selected regions. In relationship to the discussion in section 1.1, the local spatial autocorrelation shows a mixture of negative and positive spatial dependence. However, results are [16]skewed towards positive spatial price dependence, as is the case for the global indices. Overall, this implies that the price of good x in district i depends on the price of good x in proximate districts.

Spatial regression models

Before discussing results in this section, the appropriate spatial model for this study is determined from outcomes for the five models specified in section 1.1. AIC, BIC and LM criteria are used for the purpose; the lower the AIC and BIC values and the greater the LM value, the better is the model. Table 1-7 shows the resultant three most appropriate spatial models for this study, the rest of the results are in Appendix 1-A6 in the appendix. The SDM, SAR and SEM models which control for both individual and time effects are more appropriate than the other models. According to these models, rho (0.556, 0.609) and lambda (0.643) values show the presence of positive spatial price dependence. This result is consistent across all spatial models considered for the study, see findings in Tables A6-A9 in the appendix.

Results in Table 1-7 Panel A are based on the Queen spatial weights matrix while those in panel B utilised the Euclidean matrix. These are the two most different types of weights matrices given that the Queen matrix uses district boundaries while the Euclidean matrix uses the distance between the districts. For robustness checks, results in Appendix 1- A7 to 1-A9 are based on K-nearest neighbour, Rook, and Arc distance weights matrices, correspondingly. These still support the SDM, SAR and SEM models as appropriate for this study. In addition to these models, results based on Rook and K-nearest neighbour also favour the GSPRE model. Although we observe some small variations depending on the spatial weight matrix used, overall, the SDM, SAR and SEM emerge as the most appropriate models in this case.

[16] 37, 42 and 45 percent of the districts show positive dependence under the local Moran's I, Geary's C and Getis & Ord's G respectively. 28, 27 and 20 percent of the districts reported negative dependence while the remaining districts did not record a significant outcome at the 5 percent level.

Table 1-7: Appropriate spatial model[17]

Variables	SDM both	SAR both	SEM both
Panel A: Using the Queen spatial weighted matrix			
rho-spatial dep	0.556***	0.609***	
LM	4.805***	5.630***	5.557***
lambda-spatial dep			0.643***
AIC	1708.49	1725.74	1725.89
BIC	1895.02	1822.89	1822.95
Observations	360	360	360
R-squared	0.465	0.532	0.424
Panel B: Using the Euclidean matric spatial weighted matrix			
rho-spatial dep	0.433***	0.759***	
LM	3.631***	4.544***	3.854***
lambda-spatial dep			0.453***
AIC	1698.49	1842.74	1826.89
BIC	1795.02	1877.89	1878.95
Observations	360	360	360
R-squared	0.365	0.432	0.524

Source: Computation using STATA, the dependent variable is average consumer goods price

The rest of the analysis utilises the Queen matrix as the results above are consistent across the different types of spatial weights matrices. Appendix 1-A10 presents details of the Queen matrix; 2 districts share 2 borders and only 1 district shares borders with 9 districts. Essentially, it is reassuring that the three different tests of regional price distribution attest to a positive spatial price dependence. Hence, this result is incorporated in the import tariff pass-through analysis.

6.1 Comparison between the 'traditional' and 'spatial' import tariffs pass-through models

This section carries out a comparative analysis of results in Table 1-8 which are based on equations 1.21 and 1.22. These are for the 'traditional' import tariffs pass-through model which does not control for regional price dependence compared to the SAR ('spatial') model which

[17] The regressions control for import tariffs, location (rural and urban), exchange rate, money supply, industrial hubs, distance to the borders, provincial dummies, rainfall), (*** p<0.01, ** p<0.05, * p<0.1). All the dummy variables are dropped in the fixed effects models.

controls for the latter. The first four columns show results based on the fixed-effects model; this drops all the static variables. The last six columns use the ordinary least squares (OLS) regression in which the static variables are added iteratively. In all regressions, the dependent variable is the average price of all goods. The most important explanatory variable is the coefficient of import tariffs. This shows the magnitude of import tariff changes passed on to domestic goods prices.

The coefficient for import tariffs is positive and statistically significant in all models. This is 0.289 in the traditional model and 0.085 in the SAR, which means 28.9 percent and 8.5 percent of import tariff changes are passed on to domestic prices following a 1 percent increase in the import tariff rate. The observation that the 'traditional' ITPTE is larger than the one in the spatial model is consistent across the 10 regressions in Table 1-8. This finding confirms that the spatial distribution of domestic prices affects the ITPTE. Thus, a failure to control for spatial price distribution biases the ITPTE.

In columns 4 and 5 we add money supply in both models, this captures the monetary policy effect on prices. Money supply is positively correlated with prices in both models, the coefficients are 0.002 and 0.013 for the traditional and SAR models, respectively. This small effect was attributable to ineffective monetary policy as the RBZ had limited control on money supply during this multi-currency era (Confederation of Zimbabwe Industry, 2014). Import tariffs and money supply results based on OLS models in Table 1-8 columns 6-11, are qualitatively like those for fixed-effects models. When location (rural/urban dummy) is added to the model in columns 10 and 11, we find that it is positive and statistically significant in both models. Results for traditional and SAR models imply that prices are 14.82 percent and 30.56 percent higher in rural than urban areas. This outcome is likely to be driven by poor rainfall over the period 2009-2014 which could have caused food shortages and rising prices in rural areas (World Bank Climate Data Portal, 2018). Poorer transport infrastructure in the rural areas could also have contributed to the relatively high prices.

Table 1-9 below continues the analysis by focusing on the OLS regression model and adding more controls to the traditional and SAR models. In columns 1-2 we add rainfall to both the traditional model and the SAR, there is a negative relationship between rainfall and domestic prices with the traditional model producing a rainfall coefficient of (-0.075) while the SAR has a coefficient of (-0.009).

Thus, a 1 percent increase in rainfall is associated with a 7.5 percent and 0.9 percent decrease in domestic goods prices under the traditional and SAR models respectively. The introduction of the rainfall variable is also affecting the location variable as it becomes smaller and less significant. Thus, agriculture activities are of paramount importance in explaining rural/urban price variations Columns 4-5 introduce the nightlight variable which captures the level of economic activities in respective districts. The coefficients for nightlight are negative and statistically significant at the 5 percent significant level; -0.091 in the SAR model compared to -0.004 in the traditional model. Thus, districts that are in close proximity to economic activities tend to benefit from relatively low prices than those that are not.

Table 1-8: Comparison between the traditional and spatial import tariffs model

			Fixed Effects models				OLS regression models			
Variables	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR
Import tariffs	0.289**	0.085**	0.205**	0.051**	0.338**	0.017**	0.260***	0.040***	0.256***	0.049***
Money supply			0.002***	0.013**			0.001*	0.003*	0.022*	0.072*
location									1.482**	3.056**
rho		4.533***		4.765***		5.562***		4.754***		5.651***
R-squared	0.565	0.553	0.568	0.564	0.498	0.479	0.497	0.584	0.393	0.598

Source: Computation, the dependent variable is average consumer goods price (significant level *** p<0.01, ** p<0.05, * p<0.1). The model also controlled for location, provincial dummies, year dummies, and distance to major borders, distance to industrial hubs. The model uses the Queen spatial weights matrix.

Table 1-9 also introduces other controls namely distance from Harare (column 6-7), Distance to Bulawayo (column 8-9), Distance to Beitbridge (column 10-11) and provincial dummies (column 14-15). Results show that the further away a district is from Harare and Beitbridge the higher are the district's prices. Distance from Harare captures the capital city effect and the relevance of industrial hubs. Following the economic crisis of 2008 most industries closed their branches in other cities like Bulawayo and only left their Harare branches open (Dube et al., 2013 and Confederation of Zimbabwe Industry, 2013). Distance from Beitbridge captures the border effect. During 2009-2014 industrial capacity for Zimbabwe was low, most goods were being imported with 85 percent of imports originating from South Africa (see Figure 1-4). Factoring in transport and other distribution costs, districts closer to Beitbridge benefited from relatively low prices. In all models, the Beitbridge border effect on prices outweighs that of Harare e.g., in column 11 the Harare coefficient is 0.048 compared to 0.064 for Beitbridge[18].

[18] Table A8 in the appendix shows the complete set of regressions in Table 12. The last two columns control for provincial effects on goods prices. Results are not robust across models. However, prices are shown to be relatively higher in Manicaland, Mashonaland East and Mashonaland West relative to Matabeleland North province. The opposite applies to prices in Masvingo, Midlands and Matabeleland South when compared to Matabeleland North.

Appendix 1-A11 extends the results in Table 1-9 as it includes all the provinces. For robustness check of outcomes for the spatial models, Appendix 1-A12 presents estimates for empirical models in Table 1-9 but using SDM and SEM. Importantly, coefficients for import tariffs in these spatial models are also positive and statistically significant. Similar to the SAR model, the import tariff pass-through effects in SDM and SEM models are smaller than those from the traditional models.

In Tables 1-8 and 1-9, the y-variable was the average price of all goods. Hence, we extended the spatial price dependence analysis from aggregate to product level as shown in Table 1-10. The key aim is to observe if the finding on import tariffs is persistent across product groups. That is, whether the 'traditional' model overestimates the import tariff effect on prices compared to spatial models (SDM, SAR and SEM). Notably, Table 1-10 only presents results for a few products, the full set of results is presented in Appendix 1-A13 in the appendix. This follows as the results are qualitatively similar across products.

In harmony with findings in Tables 1-8 and 1-9, food, cloth and beverage prices in Table 1-10 also face incomplete ITPTEs that tend to be larger in 'traditional' compared to spatial models; albeit with varying levels of statistical significance. Below we proceed to rationalise this persistent finding of our study.

Table 1-9: Comparison between the traditional and spatial import tariffs models

Variables	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR
Import tariffs	0.260***	0.040***	0.256***	0.049***	0.256***	0.049***	0.316***	0.059***	0.339***	0.062***	0.205**	0.071**	0.329**	0.084**
rho		4.805***		6.431***		5.458***		5.873***		5.643***		5.557***		5.668***
Exchange rates	0.056	-0.778	0.082	-0.978	0.008	-0.0948	0.017	-0.059	0.038	-0.093	0.098	-0.112	0.193	-0.142
Money supply	0.001*	0.002*	0.022*	0.072*	0.042*	0.067*	0.091*	0.092*	0.036*	0.074*	0.064	0.103	0.037	0.453
location	1.112*	2.956*	1.082*	2.056*	1.094**	2.068*	1.303**	1.602	1.205**	2.106**	1.250*	1.146	1.320**	1.146**
Rainfall	-0,075**	-0.009***	-0,035**	-0.014***	-0.002**	-0.023*	-0.0053**	-0.069**	-0.0047**	-0.058**	-0.002***	-0.013**	-0.012***	-0.024**
Nightlight			-0.004***	-0.091***	-0.006***	-0.101***	-0.011***	-0.081***	-0.014***	-0.171***	-0.041***	-0.171***	-0.004***	-0.091***
Distance to Harare					0.028	0.048**	0.038	0.068**	0.028	0.048**	0.014	0.019***	0.028	0.048**
Distance to Bulawayo							-0.015**	-0.006	-0.053**	-0.056	-0.053**	-0.082*	-0.015**	-0.006
Distance to Beitbridge									0.073***	0.064*	0.029*	0.023***	0.073***	0.054*
Distance to Mutare											0.015	0.010	0.015	0.010
Bulawayo prov dum													0.529	3.078
R-squared	0.424	0.532	0.365	0.584	0.265	0.558	0.424	0.465	0.365	0.465	0.373	0.507	0.436	0.545

Source: Computation using STATA, the dependent variable is the average price of all goods (significant level *** p<0.01, ** p<0.05, * p<0.1)

Table 1-1: Robustness checking (selected products)[19]

Variables	Traditional	SDM	SAR	SEM
Panel A: Food Prices				
Import tariffs	0.171**	0.063***	0.048**	0.011*
rho		0.484***	0.501***	
LM		0.224***	0.257***	0.250***
lambda				0.552***
R-squared	0.602	0.593	0.420	0.405
Panel B: Cloth prices				
Import tariffs	0.162**	0.056***	0.057**	0.025**
rho		0.526***	0.561***	
LM		0.789***	0.847***	0.843***
lambda				0.574***
R-squared	0.726	0.464	0.429	0.561
Panel C : Beverage prices				
Import tariffs	0.143**	0.0428**	0.022**	0.011***
rho		0.373***	0.429***	
LM		0.047***	0.051***	0.053***
lambda				0.440***
R-squared	0.647	0.443	0.514	0.501

Source: Own computation using STATA, (the regressions Control for import tariffs, location (rural and urban), exchange rate, money supply, industrial hubs, distance to the borders, provincial dummies, rainfall), (significant level *** p<0.01, ** p<0.05, * p<0.1)

6.2 Explanation of the import tariffs pass through bias

This section is aimed at rationalising the wedge between the ITPTE from the 'traditional' and 'spatial' models. This hinges on the inclusion or non-inclusion of the spatial lag variable in the price model. Omission of the spatial lag in the 'traditional' model generates an omitted variable bias on regression outcomes, especially the ITPTE (Wooldridge, 2002; Green, 2012 and Clark, 2005). For the problem to be valid the omitted variable should exhibit a strong correlation with both the dependent and some independent variables in the model.

Appendix 1-A14 shows a considerable correlation between the spatial weighted price and absolute prices, and some independent variables; for example, a correlation coefficient of 0.81 (0.49) with price (import tariffs). Thus, to some extent controlling for spatial price dependence attenuates the import tariff effect in SDM, SAR and SEM models. The inherent

[19] Appendix A6 shows the full regression table of the regression estimates.

spatial weights matrix captures the shortest paths relation between 60 districts paring[20]. Events in one district will affect greatly closer districts relative to districts that are far away. If goods prices are decreasing in one district, then the decrease will be propagated to the surrounding districts. Also, the spatial weight matrix captures the distance between districts implies that the matrix controls for variations in the distributional cost, language, culture, and information across districts (Haynes, 1984).

Section 1.2 showed mechanically that the ITPTE decreases as the magnitude of spatial dependence and the distributional cost increases. Firstly, Distributional costs accrue when distributing goods from one region to another. They include transport cost, information asymmetry, packaging cost, the extent of competition, domestic taxes, regulatory costs etc. (Winters, 2000b). Due to a general tendency of clustering across our districts, a decrease in the distribution cost will be propagated across districts factoring in distance. When such changes are factored in the final price, they corroborate our finding of highly interdependent goods prices across Zimbabwean districts - positive spatial dependence shown in section 1.7.

Secondly, the magnitude of spatial dependence is underpinned by the connectedness and networks among the districts. Section 1.1 alluded to the great connectedness between districts and markets in Zimbabwe brought by the relatively small size of the country, centralised markets, strong networks in the forex market and strong market links which were harnessed by hyperinflation as firms were fighting to keep afloat of market forces.

Further support of attenuation of the ITPTE once we control for spatial price dependence in Zimbabwe hinges on the adoption of the multiple currency system and the inflation rate for 2009-2014. The year-on-year inflation rate was -0.2 percent in 2014, signifying a drop in prices (Zimbabwe National Statistics Agency, 2014). To some extent, this could have reduced some distribution costs of imported products such as transport costs and domestic tax. Such deflation was immediately transmitted across districts due to aforesaid market linkages. Furthermore, an increase in import tariffs against deflation would partly absorb the ITPTE on domestic goods prices.

In addition to the above factors that dampen the ITPTE, McCulloch et al. (2001) pointed to the extent of domestic competition, the functioning of the market, infrastructure, and domestic regulation. The policy of price control is popular in Zimbabwe, where the government controls the rising of prices through enforcing strong regulation against price increase. This inevitably compromises the transmission of import tariff changes to domestic prices.

[20] The matrix acknowledges that each district has an intrinsic degree of uniqueness due to its situation relative to the rest of the district spatial system.

7 Conclusion

The study set out to achieve two key objectives: first to investigate the nature of spatial price distribution across Zimbabwean regions (districts) over the period 2009-2014; second to investigate whether a failure to control for the nature of spatial price distribution when estimating the ITPTE biases the estimates.

Firstly, the study finds a positive spatial price dependence of domestic goods prices among Zimbabwean regions (districts), over the period 2009-2014. This finding is based on several spatial econometrics' techniques (Spatial maps; the Moran's I, Geary's C, Gertis and Ord's G statistics; Spatial Durbin model, Spatial Auto-Regressive model, Spatial Error model, Spatial Autoregressive with Spatially Autocorrelated Errors model and the Generalised Spatial Random-effects model). The results broadly implies that precise estimates of price or demand models in Zimbabwe, and especially those on the ITPTE, require factoring in the distribution of domestic goods prices. Policymakers also need to be sensitive as policies or events that change (increase) goods prices in one region (e.g. a cyclone) will be propagated across several districts which have a negative welfare effect. Such finding advocate for regional-district specific policies rather than blanket policies on issues about household welfare, inequality, inflation industrialization among others. Regions within Zimbabwe are being disproportionately affected by a similar change in import tariffs. The import tariffs effect among the regions are further propagated to the surrounding regions due to the connectedness as highlighted by a positive price spatial dependence among the regions. Implementation of a blank policy measure and strategy for example a blanket policy on reducing income inequality using a 10 percent subsidy on basic goods. Such a blanket policy is thus likely to be less effective due to the spatial dependence-connectedness of the regions. The subsidy effect is likely to be disproportionately propagated across the regions with likelihood of second, third and more round effects in the respective regions.

Secondly, the study finds evidence of an incomplete tariff pass through in Zimbabwe; a positive and significant portion of import tariffs changes are passed on to domestic goods prices. This finding is consistent with the outcomes of Malliek and Marques (2007) and Hayakawa and Ito (2015) based on developed and developing countries. However, the import tariffs pass-through effects found in this study are relatively low. That is a maximum of 33.9 percent for the traditional non-spatial model and 8 percent for spatial price dependence models. In contrast, Feenstra (1989), Kreinin (1977) and Malliek and Marques (2007) found an import tariff pass-through of around 60 percent. Districts links, networks, connectedness, and the high distribution cost-justify the large disparities. Regardless, policy-makers should be cautious of the import tariffs increase in relationship to household welfare and poverty reduction targets. Since an increase in import tariffs translates into a non-trivial increase in domestic goods prices. Countries planning to adopt a multiple currency and cash budget system should thus be aware of the likely effects of implementing such policies since they require some discipline concerning import tariff changes.

Third and more importantly, the study found that 'traditional' import tariffs pass-through models which do not account for spatial correlation of domestic goods prices tend to overestimate the ITPTE. Thus, the domestic spatial distribution of prices highly affects the ITPTE. This highlights the need to control for spatial distribution of domestic goods prices when estimation the import tariffs pass-through effect. Especially, given that the results may be informative for national socio-economic development policies.

The major weakness of the study is the failure to separate tradable and non-tradable components of products used for the analysis. The dataset used for the study includes products where some portions were produced domestically, and some were imported. However, due to the lack of a mechanism to distinguish such portions, all the products were assumed to have been imported. Depending on the degree of bias, our results should be interpreted with caution. We, however, recommend that where possible future studies can benefit from separating tradable and non-tradable components of all products before embarking on a typical analysis. In addition, future studies should take note of the geographic demarcations of the districts since this might exacerbate the price dependence if there are some demarcation overlaps. This study encountered the limitation that not all districts from the price surveys were matched to the shape-files, as the shapefiles presented some cities as composite districts. Such a move might influence the spatial price dependence due to averaging out prices of sub-districts to get a single price for the composite district.

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Appendix

1-A1: Description of the variable used for the analysis

Variable-description	Measurements	Expected relationship with goods prices	Source
Food prices	average prices of all food items per liter/per kilogram in US dollars		Zimstat (2009-2014)
Non-alcohol beverage prices	average price per unit (750 ml/350ml) of all non-alcohol beverages in US dollars		Zimstat (2009-2014)
Alcohol beverage prices	average price per unit of alcohol 750ml/350ml) in US dollars		Zimstat (2009-2014)
Cloth prices	average price per unit of cloth items in US dollars		Zimstat (2009-2014)
Footwear prices	average per unit price of footwear in dollars		Zimstat (2009-2014)
Fuel prices	average price per liter of fuel in US dollars		Zimstat (2009-2014)
Vehicle fluids	average price per liter of vehicle fluid (engine oil, brake fluid and grease) price in US dollars		Zimstat (2009-2014)
Furniture prices	average price per unit of furniture products in US dollars		Zimstat (2009-2014)
Night light	average amount of light intensity or lumens measured in lux (lx)		GIS raster files (2009-2014)
Temperature	Average temperature levels measured in degrees Celsius		GIS raster files (2009-2014)
Location	rural dummy, 1=rural and 0= urban	High price in the rural areas relative to urban area	Zimstat (2009-2014)
Exchange rate	average US$ to South African ZAR exchange rate	Positive relation between exchange rates and price	Reserve bank of Zimbabwe (2009-2014)
Money supply	average official money supply in millions of US$ as reported by the Central bank	Positive relation between money supply and prices	Reserve bank of Zimbabwe (2009-2014)
Distance	average distance between districts in kilometers	We expect lower price in districts which are closer to borders	calculations from the shapefile collected from the ArcGIS website
Import tariffs	average ad-valorem/ converted ad-valorem tariffs rate –percent of absolute price. All import tariffs were converted to ad valorem since we originally had ad valorem, specific import and mixed (partly ad valorem and partly specific) import tariff rates types. The study is using average import tariff rate, that average of bilateral, general and multilateral import tariffs rates	Positive relation between import tariffs and prices	Zimbabwe Revenue Authorities (2009-2014)
Rainfall	average rainfall received in milliliters	High price in area which receives low rainfall	Rasta file collected from ArcGIS website

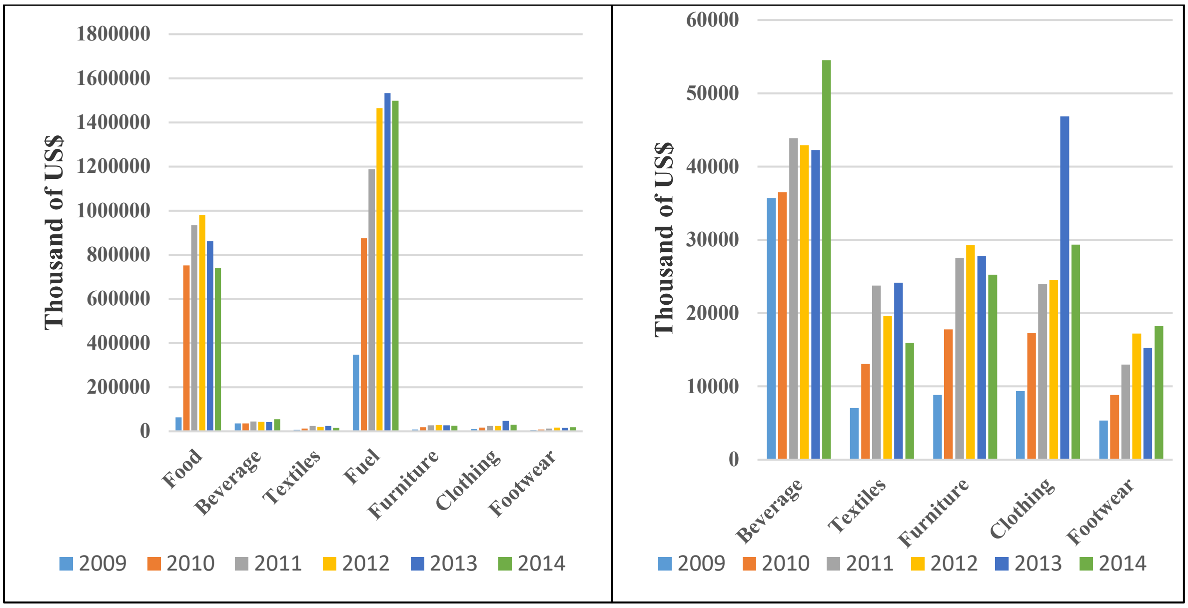
1-A2: Summary statistics

Variable		Mean	Std. Dev.	Min	Max	Observations
location	overall	0.3972	0.48	0	1	N = 360
	between		0.490	0	1	n = 60
Distance to Harare	overall	225.028	120.3872	0.0004	876	N = 360
	between		120.3872	0.0004	876	n = 60
Distance to Bulawayo	overall	294.7058	142.429	0.0005	810	N = 360
	between		142.429	0.0005	810	n = 60
Exchange rate	overall	8.578021	1.384093	6.7198	11.4568	N = 360
	between		1.384093	6.7198	11.4568	n = 60
	within		0	8.578021	8.578021	T = 6
Distance to Mutare	overall	283.9555	146.9314	0.0002	1016	N = 360
	between		146.9314	0.0002	1016	n = 60
Distance to Beitbridge	overall	344.8577	134.9184	0.000571	759	N = 360
	between		134.91	0.0005	759	n = 60
Bulawayo Province	overall	0,016	0.128	0	1	N = 360
	between		0.128	0	1	n = 60
Harare province	overall	0,016	0.128	0	1	N = 360
	between		0.128	0	1	n = 60
Manicaland province	overall	0,116	0.321	0	1	N = 360
	between		0.321	0	1	n = 60
Mashonaland central	overall	0,116	0.321	0	1	N = 360
	between		0.321	0	1	n = 60
Mashonaland east	overall	0,15	0.357	0	1	N = 360
	between		0.357	0	1	n = 60
Mashonaland west	overall	0,11	0.300	0	1	N = 360

	between		0.300	0	1	n = 60
Matabeleland North	overall	0,133	0	0	0	N = 360
	between		0	0	0	n = 60
Matabeleland South	overall	0,116	0.3214	0	1	N = 360
	between		0.321	0	1	n = 60
Midlands province	overall	0,133	0.3404	0	1	N = 360
	between		0.3404	0	1	n = 60

Source: Stata output using price surveys from ZIMSTAT 2009-2014.

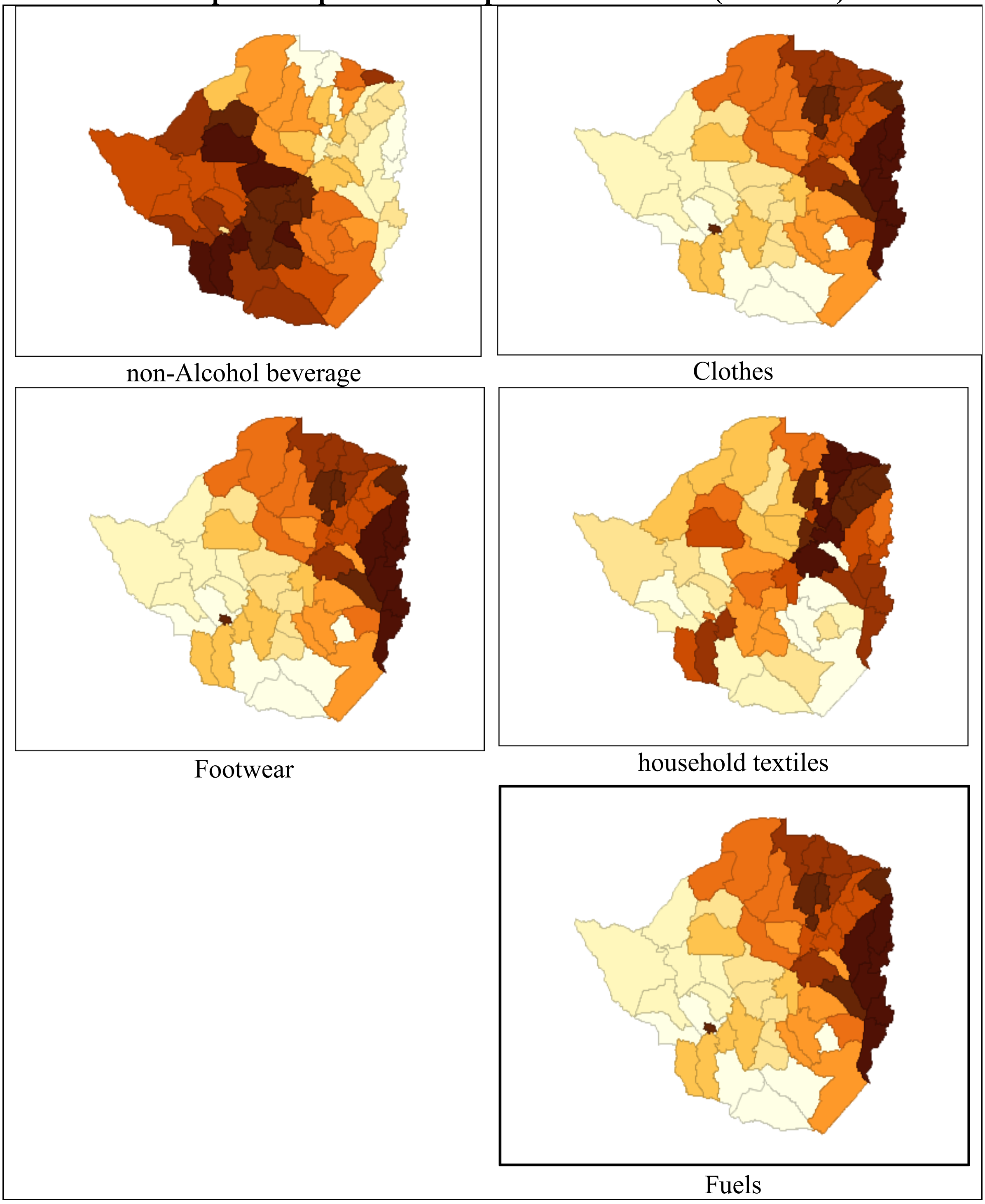
1-A3: Volume of Imports by Products



Source: Own computation using (WITS database)

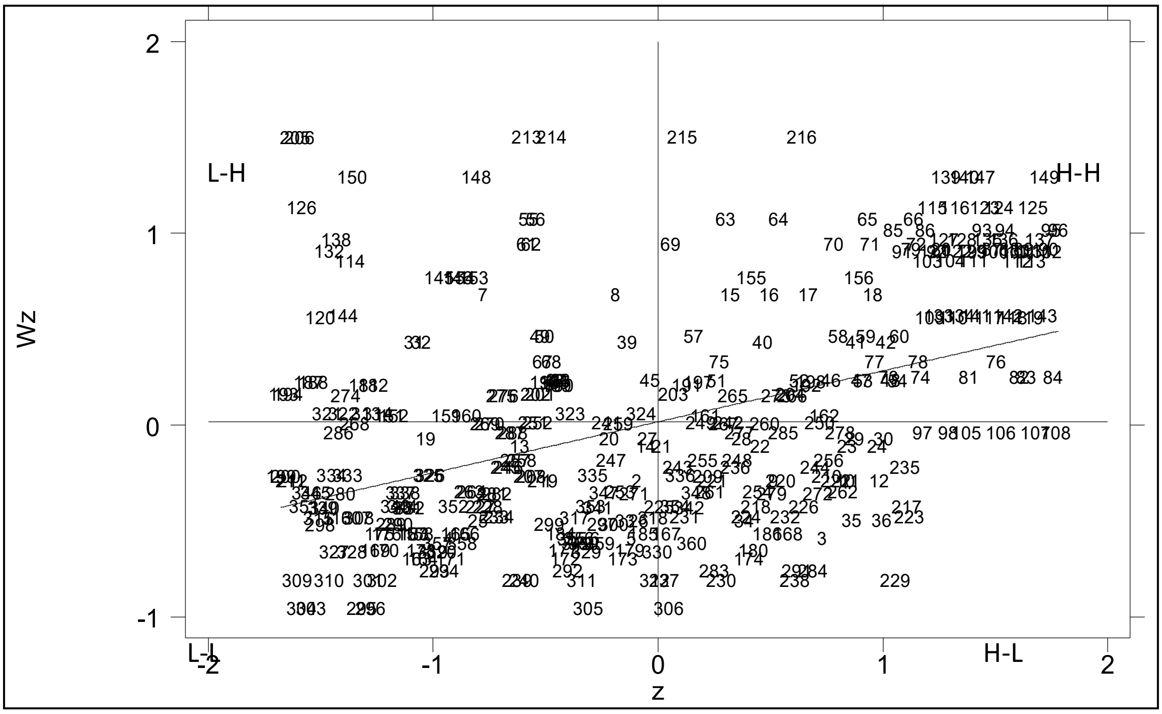
1-A.3 serves to depict that the goods used in this study are indeed tradable. It shows Zimbabwe's imports by product groups. The figure to the left (1-A.3A) includes food and fuels while the one to the right (1-A.3B) excludes the two product groups. Food and fuel have high values thus they overshadow other imports as shown in 1-A.3A hence 1-A.3B removes food and fuel. From 2009-2014 Zimbabwe was significantly importing all the products depicted above. However, food (36 percent) and fuels (57.7 percent) occupied the highest share of imports. This was partly attributed to poor harvest and increased demand for fuel linked to an influx of vehicle imports that were dominated by second-hand Japanese cars (CZI, 2013). Thus the products groups in our study (see Table 1-6 can arguably be treated as tradable over the period 2009-2014.

1-A4: Spatial maps of domestic prices in Zimbabwe (2009-2014)



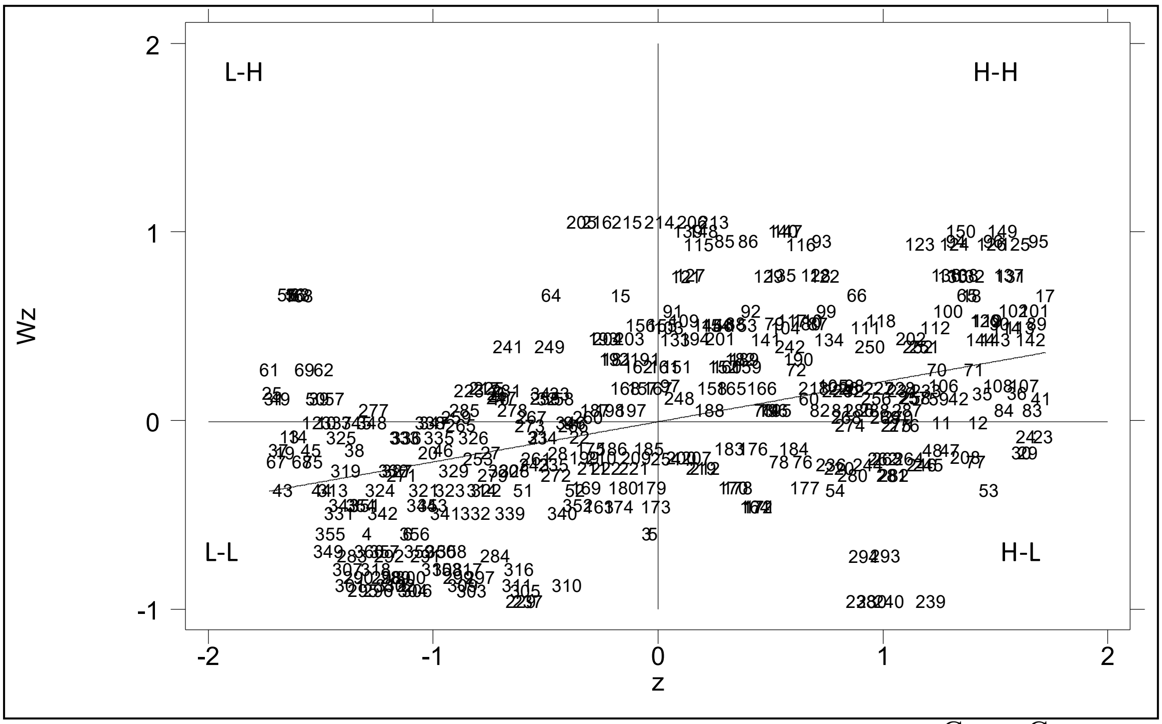
Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles

1-A5-A: Local Moran's



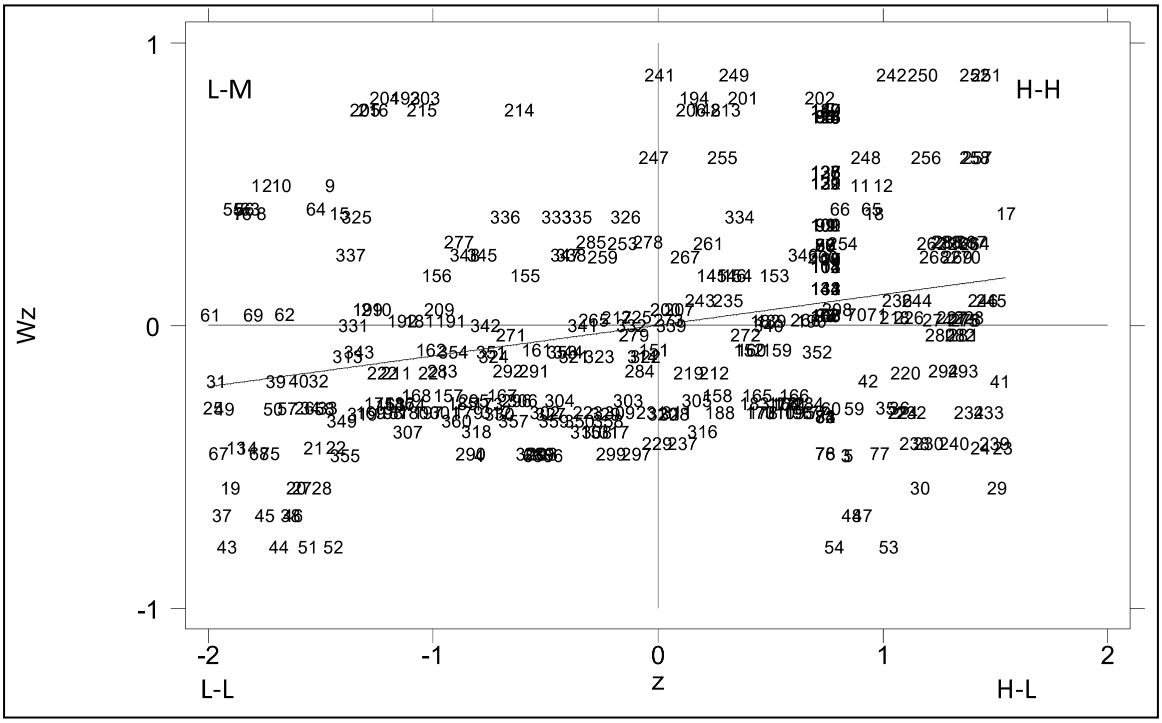
Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles Local Moran's

1-A5 –B: Local Geary C,



Source: STATA output using Zimstat price surveys data and ArcGIS shape files Local Geary C

1-A5-C: Local Getis & Ord's G



Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles - Local Getis & Ord's G

1-A6: Appropriate spatial model (queen weights matrix)

	Appendix: A3 Appropriate spatial model				
Variables	SDM_ind_fxd_effects	SDM_fxd_time_effects	SDM_re_effects	SDM_both_fxd_effects	SDM_without_effects
rho	0.832***	0.392***	0.359***	0.865***	0.842***
LM	4.852***	7.322***	8.327***	**4.805*****	4.852***
AIC	1716,27	1856,52	1879,936	**1708,49**	1716,27
BIC	1902,79	2043,05	1988,75	**1895,02**	1902,79
Observations	360	360	360	360	360
R-squared	0.439	0.434	0.265	**0.465**	0.039
Variables	SAR_fxd_ind_effects	SAR_re_effects	SAR_fxd_time_effects	SAR_fxd_both_effects	SAR_without_effects
rho	0.528***	0.526***	0.564***	0.591***	0.651***
LM	5.719***	8.380***	8.634***	**5.630*****	4.852***
AIC	1736,41	1882,61	1865,12	**1725,74**	1716,27
BIC	1833,56	1987,54	1962,27	**1822,89**	1902,79
Observations	360	360	360	360	360
R-squared	0.067	0.509	0.001	**0.532**	0.039
Variables	SEM_fe__ind_effects	SEM_re_effects	SEM_fe_time_effects	SEM_both_effects	SEM_without_effects
rho	0.534	0.471***	0.619***	0.591***	0.534
LM	5.726***	8.048***	8.083***	**5.557*****	8.048***
AIC	1741,46	1874,26	1852,16	**1725,59**	1874,26
BIC	1838,61	1979,18	1949,31	**1822,75**	1979,18
Observations	360	360	360	360	360
R-squared	0.032	0.484	0.081	**0.424**	0.484
Variables	SAC_fxd_ind_effects	SAC_fxd_time_effects	SAC_both_effects	SAC_without_effects	GSPRE_re_effects
Rho/lambda	0.591***	0.526***	0.564***	0.591***	0.649***
LM	4.852***	7.322***	4.805***	7.328***	4.526***
AIC	1716,27	1856,52	1798,49	1865,71	1875,81
BIC	1902,79	2043,05	1895,02	2060,01	1984,62
Observations	360	360	360	360	360
R-squared	0.039	0.034	0.565	0.580	0.486

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles, the dependent variable is average consumer goods price

1-A7: Appropriate spatial model (K-nearest distance weights matrix)

VARIABLES	SDM_re_effects	SDM_fxd_time_effects	SDM_both_fxd_effects	SDM_without_effects	SAR_fxd_ind_effects
rho	0.522	0.471***	0.517***	0.531***	0.731***
LM	4.528***	5.526***	**7.704*****	5.594***	4.651***
AIC	2232.828	2379.103	**1924.387**	2366.186	2222.242
BIC	2337.753	2487.914	**2024.389**	2467.224	2323.281
Observations	360	360	360	360	360
R-squared	0.519	0.018	0.264	0.042	0.064
	SAR_re_effects	SAR_fxd_time_effects	SAR_fxd_both_effects	SAR_without_effects	SEM_re_effects
Rho/lambda	0.423***	0.624***	0.663***	0.694***	0.648***
LM	4.534	5.471***	**6.669*****	4.594***	5.647***
AIC	2210.355	2363.421	**1913.851**	2363.421	2365.357
BIC	2408.546	2472.231	**2023.181**	2472.231	2336.303
Observations	360	360	360	360	360
R-squared	0.513	0.001	0.212	0.042	0.493
	SEM_fe__ind_effects	SEM_re_effects	SEM_fe_time_effects	SEM_both_effects	SEM_without_effects
lambda	0.547***	0.604***	0.547***	0.681***	0.559***
LM	5.504***	5.647***	4.581***	4.649***	5.647***
AIC	2352.735	2220.843	2363.421	2210.355	2213.851
BIC	2453.774	2321.881	2472.231	2408.546	2551.89
Observations	360	360	360	360	360
R-squared	0.015	0.493	0.137	0.195	0.493
	SAC_fxd_ind_effects	SAC_time_ind_effects	SAC_both_effects	GSPRE_re_effects	GSPRE_without_effects
lambda	0.649***	0.649***	0.619***	0.647***	0.522***
LM	4.594***	5.526***	5.564***	5.649***	**6.659*****
AIC	2357.409	2201.174	2364.708	2364.708	**1923.178**
BIC	2551.714	2395.479	2477.405	2477.405	**2102.744**
Observations	360	360	360	360	360
R-squared	0.042	0.018	0.264	0.494	0.494

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles, the dependent variable is average consumer goods price

1-**A8: Appropriate spatial model (rook weights matrix)**

VARIABLES	SDM_re_effects	SDM_fxd_time_effects	SDM_both_fxd_effects	SDM_without_effects	SAR_fxd_ind_effects
rho	0.661***	0.544	0.481***	0.627***	0.563***
LM	4.528***	4.526***	**6.692*****	4.564***	5.451***
AIC	2592.479	2524.763	**2167.666**	2671.038	2658.121
BIC	2700.67	2629.688	**2257.668**	2779.849	2759.159
Observations	360	360	360	360	360
R-squared	0.519	0.018	0.264	0.041	0.064
VARIABLES	SAR_re_effects	SAR_fxd_time_effects	SAR_fxd_both_effects	SAR_without_effects	SEM_re_effects
Rho/lambda	0.664***	0.491***	0.551***	0.434	0.371***
LM	4.534	4.471***	**7.749*****	5.592***	4.547***
AIC	2514.177	2655.355	**2502.479**	2523.313	2655.355
BIC	2764.166	2700.67	**2615.216**	2628.238	2764.166
Observations	360	360	360	360	360
R-squared	0.513	0.001	0.212	0.041	0.493
VARIABLES	SEM_fe__ind_effects	SEM_re_effects	SEM_fe_time_effects	SEM_both_effects	SEM_without_effects
lambda	0.604***	0.547***	0.481***	0.559***	0.547***
LM	5.259***	5.447***	4.531***	**7.704*****	5.647***
AIC	2655.355	2644.67	2512.777	**2166.458**	2582.479
BIC	2764.166	2745.709	2693.816	**2266.46**	2700.67
Observations	360	360	360	360	360
R-squared	0.015	0.493	0.137	0.195	0.493
VARIABLES	SAC_fxd_ind_effects	SAC_time_ind_effects	SAC_both_effects	GSPRE_re_effects	GSPRE_fe_effects
Rho/lambda	0.571***	0.515***	0.554***	0.591***	0.541***
LM	4.592***	5.526***	4.564***	**6.634*****	5.634***
AIC	2156.796	2649.344	2493.109	**2256.874**	2256.874
BIC	2745.689	2843.649	2687.414	**2619.571**	2619.571
Observations	360	360	360	360	360
R-squared	0.041	0.018	0.264	0.498	0.498

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles, the dependent variable is the average consumer goods price.

1-A9 Appropriate spatial model (Arc distance weights matrix)

VARIABLES	SDM_re_effects	SDM_fxd_time_effects	DSM_both_fxd_effects	SDM_without_effects	SAR_fxd_ind_effects
rho	0.528***	0.526***	0.691***	0.564***	0.651***
LM	5.558***	4.326***	**6.772*****	5.824***	4.811***
AIC	2709.64	2731.894	**2340.275**	2878.169	2865.252
BIC	2907.831	2836.819	**2440.277**	2986.98	2966.29
Observations	360	360	360	360	360
R-squared	0.519	0.018	0.264	0.041	0.064
VARIABLES	SAR_re_effects	SAR_fxd_time_effects	SAR_fxd_both_effects	SAR_without_effects	SEM_re_effects
rho	0.534	0.471***	0.689***	0.591***	0.647***
LM	5.392	5.391***	**6.579*****	5.521***	5.837***
AIC	2721.308	2709.64	**2652.487**	2730.444	2862.487
BIC	2822.347	2907.831	**2571.297**	2835.369	2971.297
Observations	360	360	360	360	360
R-squared	0.513	0.001	0.212	0.041	0.493
VARIABLES	SEM_fe__ind_effects	SEM_re_effects	SEM_fe_time_effects	SEM_both_effects	SEM_without_effects
rho	0.659***	0.647***	0.581***	0.704***	0.647***
LM	4.539***	3.691***	4.211***	**7.704*****	4.327***
AIC	2339.067	2851.801	2719.908	**2702.487**	2709.64
BIC	2639.069	2952.84	2820.947	**2607.297**	2907.831
Observations	360	360	360	360	360
R-squared	0.015	0.493	0.137	0.195	0.493
VARIABLES	SAC_fxd_ind_effects	SAC_time_ind_effects	SAC_both_effects	GSPRE_re_effects	GSPRE_without_effects
rho	0.591***	0.526***	0.564***	0.649***	0.649***
LM	3.943***	3.446***	4.744***	5.059***	4.618***
AIC	2829.739	2856.475	2700.24	2863.774	2863.774
BIC	2718.632	3050.78	2894.545	2976.471	2976.471
Observations	360	360	360	360	360
R-squared	0.041	0.018	0.264	0.494	0.494

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles, the dependent variable is average consumer goods price

1-A10: Details of the Queen weighted matrix

Number of borders shared	Observation
2	2
3	8
4	11
5	12
6	13
7	9
8	4
9	1
Sum	60

Source: Stata output using the shapefile from https://www.arcgis.com

1-A11: Comparison between the traditional and spatial import tariffs models (Queen spatial weighted matrix)

Variables	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR	Traditional	SAR
Import tariffs	0.260***	0.040***	0.256***	0.049***	0.256***	0.049***	0.316***	0.059***	0.339***	0.062***	0.205**	0.071**	0.329**	0.084**
rho		4.805***		6.431***		5.458***		5.873***		5.643***		5.557***		5.668***
Exchange rates	0.056	-0.778	0.082	-0.978	0.008	-0.0948	0.017	-0.059	0.038	-0.093	0.098	-0.112	0.193	-0.142
Money supply	0.001*	0.002*	0.022*	0.072*	0.042*	0.067*	0.091*	0.092*	0.036*	0.074*	0.064	0.103	0.037	0.453
location	1.112*	2.956*	1.082*	2.056*	1.094**	2.068*	1.303**	1.602	1.205**	2.106**	1.250*	1.146	1.320**	1.146**
Rainfall	-0,075**	-0.009***	-0,035**	-0.014***	-0.002**	-0.023*	-0.0053**	-0.069**	-0.0047**	-0.058**	-0.002***	-0.013**	-0.012***	-0.024**
Nightlight			-0.004***	-0.091***	-0.006***	-0.101***	-0.011***	-0.081***	-0.014***	-0.171***	-0.041***	-0.171***	-0.004***	-0.091***
Distance to Harare					0.028	0.048**	0.038	0.068**	0.028	0.048**	0.014	0.019***	0.028	0.048**
Distance to Bulawayo							-0.015**	-0.006	-0.053**	-0.056	-0.053**	-0.082*	-0.015**	-0.006
Distance to Beitbridge									0.073***	0.064*	0.029*	0.023***	0.073***	0.054*
Distance to Mutare											0.015	0.010	0.015	0.010
Bulawayo prov dum													0.529	3.078*
Harare province dum													-4.585*	-2.122**
Manicaland prov dum													1.914***	2.520*
Mashonaland central prov dum													0.237	4.62**
Mashonaland east prov dum													0.824	3.50**
Mashonaland west prov dum													-0.294	-2.755*
Masvingo prov dum													-2.911*	-3.453*
Matabeleland south dum													-2.811***	-1.823*
Midlands prov dum													-3.105***	3.255*
R-squared	0.424	0.532	0.365	0.584	0.265	0.558	0.424	0.465	0.365	0.465	0.373	0.507	0.436	0.545

Source: STATA output using Zimstat price surveys data and ArcGIS shape files, the depend variable is average consumer goods (significant level *** $p<0.01$, ** $p<0.05$, * $p<0.1$)

1-A12: SDM and SEM spatial price distribution models

Variables	SDM	SEM	SDM	SEM	SDM	SEM	SDM	SEM	SDM	SEM	SDM	SEM	SDM	SEM	SDM	SEM	SDM	SEM
Import tariffs	0.10**	0.09**	0.09**	0.06**	0.091**	0.010**	0.0166***	0.091***	0.013***	0.097***	0.017***	0.059***	0.083***	0.062***	0.0905**	0.071**	0.012**	0.084**
rho	6.7***	5.6***	5.02***	4.8***	5.821***	5.557***	5.427***	4.668***	5.838***	5.458***	4.433***	5.873***	4.759***	5.643***	4.867***	5.537***	5.436***	5.668***
Exchange rates			0.193	-0.142	1.482**	3.056**	0.056	-0.778	0.008	-0.0948	0.017	-0.059	0.038	-0.093	0.098	-0.112	0.193	-0.142
Money supply					4.754***	5.651***	0.001*	0.002*	0.042*	0.067*	0.091*	0.092*	0.036*	0.074*	0.064	0.103	0.037	0.453
location					0.393	0.598	1.112*	2.956*	1.094**	2.068*	1.303**	1.602	1.205**	2.106**	1.250*	1.146	1.320**	1.146**
Rainfall							-0,075**	-0.009***	-0.002**	-0.023*	-0.0053**	-0.069**	-0.0047**	-0.058**	-0.002***	-0.013**	-0.012***	-0.024**
Nightlight									-0.006***	-0.101***	-0.011***	-0.081***	-0.014***	-0.171***	-0.041***	-0.171***	-0.004***	-0.091***
Distance to Harare									0.028	0.048**	0.038	0.068**	0.028	0.048**	0.014	0.019***	0.028	0.048**
Distance to Bulawayo											-0.015**	-0.006	-0.053**	-0.056	-0.053**	-0.082*	-0.015**	-0.006
Distance to Beitbridge													0.073***	0.064*	0.029*	0.023***	0.073***	0.054*
Distance to Mutare															0.015	0.010	0.015	0.010
Bulawayo prov dum																	0.529	3.078
Harare province dum																	-4.585*	2.122
Manicaland prov dum																	1.914***	2.520
Mashonaland central prov dum																	0.237	4.62**
Mashonaland east prov dum																	0.824	3.50**
Mashonaland west prov dum																	-0.294	-2.755*
Masvingo prov dum																	-2.911*	-3.453
Matabeleland south dum																	-2.811***	-1.823
Midlands prov dum																	-3.105***	3.255
R-squared		0.518	0.438	0.549	0.418	0.495	0.424	0.532	0.265	0.558	0.424	0.465	0.365	0.465	0.373	0.507	0.436	0.545

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles., the dependent variable is average goods price (significant level *** p<0.01, ** p<0.05, * p<0.1

1-A13: Regression estimates

	Panel A: Food Prices			
Variables	Traditional	SDM	SAR	SEM
Import tariffs	0.271**	0.063***	0.048**	0.011*
exchange rate	0.0176	0.0416*	0.126**	0.00985***
money supply	0.0192**	0.0123***	0.0219**	0.0128***
rainfall	-0.032***	-0.020***	-0.004**	-0.008***
rho		0.484***	0.501***	
LM		0.224***	0.257***	0.250***
lambda				0.552***
R-squared	0.602	0.593	0.420	0.405
	Panel B: Cloth prices			
Import tariffs	0.362**	0.056***	0.057**	0.025**
exchange rate	0.0347	-0.0471	0.202*	0.219**
money supply	0.00952**	-0.0100	-0.00130	-9.71e-05
rainfall	-0.033***	-0.0135***	-0.00232	-0.00237
rho		0.526***	0.561***	
LM		0.789***	0.847***	0.843***
lambda				0.574***
R-squared	0.726	0.464	0.429	0.561
	Panel C : Alcohol Beverage			
Import tariffs	0.432**	0.0428**	0.022**	0.011***
exchange rate	0.0132	0.116**	0.00885	
money supply	0.00161***	0.00197	-0.00132	
rainfall	-0.031***	-0.0044***	-0.0078	
rho		0.373***	0.429***	
LM		0.047***	0.051***	0.053***
lambda				0.440***
R-squared	0.647	0.443	0.514	0.501

	Panel D : Furniture			
Import tariffs	0.390**	0.0336***	0.140***	0.0529***
exchange rate	6.911*	12.89*	3.808	1.568
money supply	-0.00760	-0.0284	-0.0186	-0.0160
rainfall	-0.011***	-0.196	0.00155	0.00688
rho		0.582***	0.650***	
LM		0.035***	0.057***	0.032***
lambda				0.702***
R-squared	0.362	0.316	0.431	0.610
	Panel E : Vehicle Fluids			
Import tariffs	0.208**	0.095***	0.061***	0.049***
exchange rate	0.103	0.433	0.101	0.161
money supply	0.00875**	-0.022	0.0136	0.0242
rainfall	-0.065	-0.00369	2.59e-05	-0.00346
rho		0.490***	0.499***	
LM		0.962***	1.039***	1.031***
lambda				0.520***
R-squared	0.480	0.523	0.461	0.482
	Pane F : Household Textile			
Import tariffs	0.251***	0.032***	0.081***	0.047***
exchange rate	0.0891	0.0633	0.229*	0.238*
money supply	0.0131**	-0.00692	-0.00272	-0.0282
rainfall	-0.098*	-0.0226***	-0.00531*	-0.00467
rho		0.496***	0.523***	
LM		1.426***	1.524***	1.521***
lambda				0.533***
R-squared	0.345	0.516	0.479	0.499
	Panel G : Fuel			
Import tariffs	0.277***	0.062*	0.043***	0.08***
exchange rate	0.378	1.262*	0.751**	0.675***
money supply	0.00125	-0.00720	-0.00219	-0.00106
rainfall	-0.074	-0.0126	0.00388	-0.000883

rho		0.507***	0.614***	
LM		5.553***	6.861***	6.748***
lambda				0.648***
R-squared	0.363	0.409	0.562	0.501
	Panel H : Footwear			
Import tariffs	0.331**	0.033***	0.065***	0.032***
exchange rate	0.0913	0.229	0.249*	0.252**
money supply	0.0108**	-0.00965	-0.00179	-0.00129
rainfall	-0.034	-0.0133**	-0.00854	-0.00153
rho		0.481***	0.532***	
LM		1.100***	1.234***	1.226***
lambda				0.550***
R-squared	0.489	0.528	0.552	0.551
	Panel I : Non-alcohol Beverage			
Import tariffs	0.695**	0.061***	0.027***	0.014***
exchange rate	-0.0134	-0.128	0.0529	0.0898**
money supply	0.00270	-0.00180	-0.00201	-0.00194
rainfall	-0.029	-0.00618**	-0.00113	-0.000688
rho		0.574***	0.627***	
LM		0.153***	0.171***	0.167***
lambda				0.662***
R-squared	0.452	0.471	0.487	0.359

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles. , the depend variable is average consumer goods (significant level *** p<0.01, ** p<0.05, * p<0.1)

1-A14: Correlation matrix

	Prices	Tariffs	Money supply	Spatial weighted price	Rainfall	Distance to Beitbridge	Location
Prices	1.0000						
Tariffs	0.4438	1.0000					
Money supply	0.4013	0.8857	1.0000				
Spatial weighted price	0.8173	0.4912	0.4672	1.0000			
Rainfall	-0.1935	0.0018	0.0041	-0.3858	1.0000		
Distance to Beitbridge	0.2366	-0.0006	-0.0040	0.4563	-0.4430	1.0000	
Location	0.0325	0.0007	0.0041	0.0470	-0.2201	0.0475	1.0000

Source: STATA output using Zimstat price surveys data and ArcGIS shapefiles.