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A Generalized Dynamic Inverse AIDS Model for Fresh Fruits and Vegetables: An Application to the U.S. Bell Pepper Industry

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Abstract

A novel approach is developed to evaluate the effect of changes in consumption habits on the price flexibilities of fresh fruits and vegetables. Thus, the traditional Inverse AIDS model is augmented with own- and cross-consumption habits. Results of the dynamic AIDS models suggest that habit formation plays a vital role in the magnitude of the own- and cross-price flexibilities. The D-IAIDS model with unrestricted own- and cross-habit formation outperformed the static version and the dynamic model developed by Holt and Goodwin (1997). Similarly, it generated, generally, smaller (bigger) own (cross) price flexibilities than the static and H&G version. For the bell pepper industry, results indicate that the U.S. consumers substitute more easily the locally produced bell pepper with imported bell pepper than the other way around. The local bell pepper is nearly two times more substitutable by imports from the ROW than by imports from Mexico. Changes in the consumption habits of bell pepper, at the aggregated level, make the demand for bell pepper (own-price flexibilities) more inflexible/elastic. Likewise, an increase of bell pepper consumption habits, at the aggregate level, increase the substitution possibilities among sources. As hypothesized, changes on the own- and cross consumption habits affect the price flexibilities in different magnitude and direction, which means that some of the aggregated habit effects are zero because the specific habit effects canceled each other. The cross-price flexibilities are affected more by changes in the habits of buying the Mexican bell pepper than changes in the habits of buying bell pepper from other sources. For the own-price flexibilities, the greatest habit effects come from changes in own consumption habits.

Key Words: Inverse AIDS, Bell Pepper, habit formation, own- and cross-habit, habit flexibility, substitution possibilities.

JEL Classification: Q11, Q17, Q18

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1 Introduction

For many fruits and vegetables, such as bell pepper, quantities are predetermined due to the lag in production decisions and the high level of perishability. In the short run, from one up to four months, bell pepper quantities are fixed because farmers cannot adjust production instantaneously, nor can they store it like corn or soybeans. This indicates that farmers cannot adjust supply in a one month-period in response to changes in prices. Therefore, prices need to respond to relative changes of short run quantity supplied or demanded to clear the market.

When quantities are predetermined, an inverse demand system model would be appropriate as argued by Huang, (1988), Barter and Bettendorf (1989), Moschini and Vissa (1992), Eales and Unnevehr (1991 and 1993), and Park and Thurman (1999). The inverse AIDS model uses the assumption that in the short run prices must adjust to clear the market from an excess or deficit of a commodity. In other words, the model assumes that prices adjust immediately when quantities available in the market change from the expected value. This approach does not provide a realistic description of how the consumers behave. Consumers delay in reacting to shocks in the available quantity of fresh fruit and vegetables, which makes the adjustments toward a new equilibrium take several periods.

Intermediaries, at the warehouse level, responsible for connecting suppliers with the final consumers, might have early commitments for a fixed quantity at a fixed price. Thus, changes in the supply of fresh fruits and vegetables might not reflect instantaneous equilibrium adjustments through price.

Lack of information could also be another reason why prices do not adjust immediately. For example, suppose that farmers in Mexico increase production of vegetables by 10% in the next production cycle. Since the intermediary, at the warehouse level, does not have that information at the beginning of the harvest season, he might negotiate prices that are above the equilibrium level. Eventually, he will discover the excess supply, which leads to a price renegotiation to clear the market.

Based on the problems described above, a dynamic specification of the inverse AIDS model could be more appropriate. Indeed, Deaton and Muellbauer (1980b) have suggested generalizing their static model by adding dynamic elements and other factors to explain consumer behavior in a more theoretically consistent[1] and empirically robust manner. Later, Ray (1983) was able to specify a dynamic inverse AIDS model with short-run habits formation. Building upon their methodology, Holt and Goodwin (1997) generalized the inverse AIDS model to include short-run and long-run habit formation.

Another dynamic specification more recently developed for the Inverse AIDS is the ECM[2]-IAIDS model developed by Karagiannis et al. (2000). This method borrows from the recent developments in cointegration techniques. It is extraordinarily powerful for demand equation systems with non-stationary data. The Granger representation theorem suggests that, to justify the use of cointegration techniques, at least one share equation should be cointegrated of some degree. Thus, this study does not use the ECM-IAIDS model because the data does not have a unit root process, nor are the variables cointegrated (see appendix 1).

[1] He made the argument of "theoretically consistent" because most empirical applications using the AIDS model tend to reject the homogeneity and symmetry restrictions.
[2] Error Correction Model

The influence of habit formation on the magnitude of the price flexibilities is calculated by using Holt and Goodwin (1997) dynamic models. However, given an identified limitation to their approach, an alternative specification is developed that incorporates the influence of own- and cross-habit formation. The model developed here can be useful, not only for bell pepper analysis, but for the examination of all fruits and vegetables.

The consumption of fruits and vegetables in the United States is highly seasonal. Thus, the Inverse AIDS model requires an optimal specification to control for seasonality. Since production depends on temperature, a logical step is the use of seasonal dummy variables (spring, summer, winter, and fall). In addition, the consumption of fruits and vegetables depends on festivities, weather, and holidays. Therefore, another plausible specification is to consider monthly dummy variables. Some researchers have used harmonic specifications (Sin and Cos) to control for seasonality (Kesavan and Buhr, 1995). Others have removed seasonality using the X-11 procedure or another method (Holt and Goodwin, 1997). Seasonality parameters are typically introduced as shifters in the parameter intercept "a_i" of Inverse AIDS model. In this study we augmented the model with monthly dummy variables as follows:

$$a_i^* = a_i + \delta_{i1} D_{Spring} + \delta_{i2} D_{Summer} + \delta_{i3} D_{Fall} + \vartheta_i trend.$$

2 Dynamic Specification for the Static Inverse AIDS Model

This study extends the static Inverse AIDS model to an appropriate dynamic specification by following the approach of Holt and Goodwin (1997), Ray (1983), Pollak and Wales (1969), Manser (1976), Green et al. (1978), and Blanciforti and Green (1983).

2.1 Dynamic Specification with Linear Habit Formation

The first step to incorporate dynamics in the Inverse AIDS model is the linear specification of consumption habit effects. Thus, the term μ_{t-1} is incorporated into the linear portion of the model as follows:

$$w_i = \alpha_i^* + \alpha_i^{**}\mu_{t-1} + \sum_j \gamma_{ij} Lnq_j + \beta_i LnQ \qquad (1)$$

where, $LnQ = \alpha_0 + \sum_j(\alpha_j^* + \alpha_j^{**}\mu_{t-1})Lnq_j + 0.5\sum_i\sum_j \gamma_{ij} Lnq_i Lnq_j$,

$\mu_{t-1} = \sum_j lnq_{jt-1}$,

$\alpha_i^* = \alpha_i + \sum_{s=1}^{11} \delta_{is} D_s + \delta_i * trend$, and

$\alpha_j^* = \alpha_j + \sum_{s=1}^{11} \delta_{js} D_s + \delta_j * trend$.

The term μ_{t-1} is the lagged aggregated per capita consumption in logarithmic form, with lnq_{jt-1} denoting lagged per capita quantity consumed of the j_{th} good in logarithmic form. The restrictions of the simple Inverse AIDS model apply here. Thus, the adding up assumption requires $\sum_i \alpha_i^* = 1$ and $\sum_i \alpha_i^{**} = 0$.

The H&G D-IAIDS model with linear habits implies that the effect of the lagged consumptions (*e.g.*, Lnq_{mext-1}, Lnq_{usat-1}, Lnq_{rowt-1}) are the same for a given market share equation. More clearly, the expression $\alpha_i^{**}\mu_{t-1}$ is as follows:

$\alpha_i^{**}\mu_{t-1} = \alpha_i^{**}LnQmex_{t-1} + \alpha_i^{**}LnQusa_{t-1} + \alpha_i^{**}LnQrow_{t-1}$, which is equivalent to

$\alpha_i^{**}\mu_{t-1} = \alpha_i^{**}(LnQmex_{t-1} + LnQusa_{t-1} + LnQrow_{t-1})$.

It is hypothesized that a better approach to linearly specify habit formation in the static IAIDS model is by augmenting the intercept parameter with specific lagged consumptions (Lnq_{jt-1}) instead of aggregated lag consumption (μ_{t-1}). Phrased differently, this study assumes that the lagged consumption effect of the jth good will be different than for the ith product on the

expenditure share, which contrasts with Holt and Goodwin (1997) and Ray (1983). Thus, the dynamic IAIDS model with simple linear own- and cross-habit formation is as follows:

$$w_i = \alpha_i^* + \sum_j \alpha_{ij}^{**} Lnq_{jt-1} + \sum_j \gamma_{ij} Lnq_j + \beta_i ln\tilde{Q} \quad (2)$$

where $Ln\tilde{Q} = \alpha_0 + \sum_j (\alpha_j^* + \sum_i \alpha_{ij}^{**} Lnq_{jt-1}) Lnq_j + 0.5 \sum_i \sum_j \gamma_{ij} Lnq_i Lnq_j$,

$\alpha_i^* = \alpha_i + \sum_{s=1}^{11} \delta_{is} D_s + \delta_{i12} * trend$, and

$\alpha_j^* = \alpha_j + \sum_{s=1}^{11} \delta_{js} D_s + \delta_{j12} * trend$.

Notice that this specification requires more parameters than H&G specification. For example, this approach requires n habit parameters (n goods), while H&G requires only one (the aggregate habit parameter). In the empirical application for bell pepper, it is as follows:

$$\sum_j \alpha_{ij}^{**} Lnq_{jt-1} = \alpha_{imex}^{**} Lnq_{mext-1} + \alpha_{iusa}^{**} Lnq_{usat-1} + \alpha_{irow}^{**} Lnq_{rowt-1} \quad (3)$$

Although adding up requires that $\sum_i \alpha_{ij}^{**} = 0$, this study also considers another approach. For equation 2, the restriction $\sum_i \sum_j \alpha_{ij}^{**} = 0$ allows habits to be unrestricted at the aggregated level, which is equivalent to the restriction $\sum_i \alpha_i^{**} = 0$ used in H&G model (eq. 1). The latter restriction approach for the parameter α_{ij}^{**} is similar to the approach used by Blanciforti and Green (1983). They do not impose adding up on the α_i^{**} parameter because they used only lagged own-quantity effects in each equation. Alessie and Kapteyn (1991) questioned the model of Blanciforti and Green (1983) because, according to them, it is not possible to impose adding up in the AIDS model and have habit formation at the same time without restricting the sum of $\alpha_i^{**}$to zero. Holt and Goodwin (1997) circumvent this problem by using a one-period lag of the aggregated cconsumption habits. In a way, this study is merging Blanciforti and Green (1983) with the Holt and Goodwin (1997) approach to account for unrestricted habit at the aggregated level.

This study compare the dynamic IAIDS model conditioned to own- and cross-habit formation fully restricted (R: $\sum_i \alpha_{ij}^{**} = 0$) against the proposed version with unrestricted habits.

2.2 Short-Run Dynamic IAIDS with Behavioral Habit Formation

The problem with the previous habit linear specification is that it is not behavioral. Producers, intermediaries, and policy-makers might be interested in understanding how changes in consumption habits affect the magnitude of the own- and cross-price flexibilities. Thus, another approach is required. Ray (1983) and Holt and Goodwin (1997) introduced behavioral habit formation by modifying the distance function specified by Deaton and Muellbauer (1980) and Eales and Unnevehr (1991), respectively. Thus, they augmented the distance function with previous consumption levels and coefficients that capture linear and non-linear habit effects. Thus, from the modified distance function they derived budget share equations conditioned to short-run and long-run habit formation. The inverse AIDS model with short run habit formation (μ_{t-1}) is as follows:

$$w_{it} = \alpha_i^* + \alpha_i^{**}\mu_{t-1} + \sum_j(\gamma_{ij} + \theta_{ij}\mu_{t-1})Lnq_j + (\beta_i + \eta_i\mu_{t-1})LnQ_t^* \qquad (4)$$

where,

$$LnQ_t^* = \alpha_0 + \sum_j \omega_j Lnq_{jt-1} + \sum_j\left(\alpha_j^* + \alpha_j^{**}\mu_{t-1}\right)Lnq_j + \frac{1}{2}\sum_i\sum_j(\gamma_{ij} + \theta_{ij}\mu_{t-1})Lnq_i Lnq_j.$$

$$\mu_{t-1} = \sum_j lnq_{jt-1},$$

$$\alpha_i^* = \alpha_i + \sum_{s=1}^{11}\delta_{is}D_s + \delta_i * trend, \text{ and}$$

$$\alpha_j^* = \alpha_j + \sum_{s=1}^{11}\delta_{js}D_s + \delta_j * trend.$$

In the quantity index (LnQ^*), Holt and Goodwin (1997) incorporated the term Lnq_{jt-1} to capture the specific habit effects, which contrast with Ray (1983)'s specification.

The habit effects implanted in equation 4, hereinafter SR-D-IAIDS, are referred by many researchers as "*short memory*" because only a one-period lag ($\mu_{t-1}, Lnq_{j_{t-1}}$) is allowed to condition current allocation decisions.

The parameters α_i^{**}, θ_{ij}, η_i and ω_n capture the habit effect of past consumption at the aggregate and specific level. The parameter θ_{ij} allows the own- and cross-quantity effects to vary due to changes in lagged aggregate consumption (μ_{t-1}). The parameter η_i allows the marginal consumption scale effect (β_i) to change as the past aggregated consumption (μ_{t-1}) changes. Additionally, the parameter ω_i is intended to capture the specific habit effect.

The IAIDS model with linear habit formation (eq. 1) is nested within the SR-D-IAIDS model (eq. 4). Thus, the following restrictions reduce equation (4) to (1):

- $\theta_{i1} = \cdots = \theta_{in} = 0$, for *i* equal to 1,…, *n*;
- $\omega_i = \cdots = \omega_n = 0$; and
- $\eta_i = \cdots = \eta_i = 0$.

The theoretical restriction used by H&G in their SR-D-IAIDS is as follows:

- Adding up: $\sum_i \alpha_i^* = 1$, $\sum_i \alpha_i^{**} = 0$, $\sum_i \gamma_{ij} = \sum_i \theta_{ij} = 0$, $\sum_i \beta_i = \sum_i \eta_i = 0$;
- Homogeneity: $\sum_j \gamma_{ij} = \sum_j \theta_{ij} = 0$; and
- Symmetry: $\gamma_{ij} = \gamma_{ji}$, $\theta_{ij} = \theta_{ji}$.

As before, this study hypothesizes that a better approach to incorporate behavioral short-run habit formation in the static IAIDS model is by augmenting it with specific lagged consumptions habits (Lnq_{jt-1}). Thus, this research proposes an alternative to the H&G SR-D-IAIDS model, which is hereafter called the *SR-D-IAIDS model with own- and cross-habit formation.*

The proposed SR-D-IAIDS model is derived by following closely Holt and Goodwin (1997) approach. The specific consumption habits (Lnq_{jt-1}) are incorporated into the preference

distance function. After plugging in the own- and cross-consumption habits, the distance function is parameterized to make its properties equivalent to the cost function. The derivative of the parameterized distance function with respect to Lnq_j yielded the compensated demand for good j. The inversion of the distance function at the optimum level yielded the direct utility function. Substituting the direct utility function into the compensated demand of product j yielded the uncompensated SR-D-IAIDS model conditioned to own- and cross-habit formation, which has the following form:

$$w_i = \alpha_i^* + \sum_j \alpha_{ij}^{**} Lnq_{jt-1} + \sum_j (\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij_{jt-1}} Lnq_{jt-1}) Lnq_j + (\beta_i + \sum_j \eta_{ij} Lnq_{jt-1}) Ln\ddot{Q}_t^* \quad (5)$$

where,

$$Ln\ddot{Q}_t^* = \alpha_0 + \sum_j (\alpha_j^* + \sum_j \alpha_{ij}^{**} Lnq_{jt-1}) Lnq_j + \frac{1}{2} \sum_i \sum_j (\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij_{jt-1}} Lnq_{jt-1}) Lnq_i Lnq_j$$

To simplify notation and ease comparison with H&G SR-D-IAIDS model, let us replace Lnq_{jt-1} with μ_{jt-1}. Thus, the proposed model is as follows:

$$w_i = \alpha_i^* + \sum_j \alpha_{ij}^{**} \mu_{jt-1} + \sum_j (\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij_{jt-1}} \mu_{jt-1}) Lnq_j + (\beta_i + \sum_j \eta_{ij} \mu_{jt-1}) Ln\breve{Q}_t^* \quad (6)$$

where,

$$Ln\breve{Q}_t^* = \alpha_0 + \sum_j (\alpha_j^* + \sum_j \alpha_{ij}^{**} \mu_{jt-1}) Lnq_j + \frac{1}{2} \sum_i \sum_j (\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij_{jt-1}} \mu_{jt-1}) Lnq_i Lnq_j$$

$$\mu_{jt-1} = lnq_{jt-1},$$

$$\alpha_i^* = \alpha_i + \sum_{s=1}^{11} \delta_{is} D_s + \delta_i * trend, \text{ and}$$

$$\alpha_j^* = \alpha_j + \sum_{s=1}^{11} \delta_{js} D_s + \delta_j * trend.$$

Notice that under this specification the own- and cross-consumption habits are allowed to affect each equation at different magnitudes, which contrasts with the H&G SR-D-IAIDS model. In this empirical application, the short-run own- and cross-consumption habit terms are as follows:

$$\sum_j \alpha_{ij}^{**}\mu_{jt-1} = \alpha_{i1}^{**}\mu_{mext-1} + \alpha_{i2}^{**}\mu_{usat-1} + \alpha_{i3}^{**}\mu_{rowt-1}, \quad (7)$$

$$\sum_{j_{t-1}} \theta_{ij_{jt-1}}\mu_{jt-1} = \theta_{ij1}\mu_{mext-1} + \theta_{ij2}\mu_{usat-1} + \theta_{ij3}\mu_{rowt-1}, \quad (8)$$

$$\sum_j \eta_{ij}\mu_{jt-1} = \eta_{i1}\mu_{mext-1} + \eta_{i2}\mu_{usat-1} + \eta_{i3}\mu_{rowt-1}. \quad (9)$$

Notice that the proposed dynamic model allows the specific habit formation to affect current allocation without having to specify the term $\sum_i \omega_i Lnq_{it-1}$ in the quantity index. In addition, the model is capturing the aggregated effect of habit formation but allowing the specific habit to have differentiated effects on the expenditure share equations, which contrasts with the H&G model. Thus, if the term $\sum_i \omega_i Lnq_{it-1}$ is eliminated from the H&G SR-D-IAIDS model, their model would be nested within the proposed dynamic short-run specification. Thus, the following restrictions in equation (6) will yield the modified H&G model:

For the term $\sum_j \alpha_{ij}^{**}\mu_{jt-1}$ impose the restriction: $\alpha_{i1}^{**} = \alpha_{i2}^{**} = \cdots = \alpha_{in}^{**}$,

for the term $\sum_{j_{t-1}} \theta_{ij_{jt-1}}\mu_{jt-1}$ impose the restriction: $\theta_{ij1_{t-1}} = \theta_{ij2_{t-1}} = \cdots = \theta_{ijn_{t-1}}$, and

for the term $\sum_j \eta_{ij}\mu_{jt-1}$ impose the restriction: $\eta_{i1} = \eta_{i2} = \cdots = \eta_{in}$.

For example, in the bell pepper empirical application, the imposition of the previous restrictions on the SR-D-IAIDS model (eq. 6) imply that the equations 7, 8, and 9 becomes:

$$\alpha_i^{**}\mu_{t-1} = \alpha_i^{**}\mu_{mext-1} + \alpha_i^{**}\mu_{usat-1} + \alpha_i^{**}\mu_{rowt-1} = \alpha_i^{**}Lnq_{t-1}^{mex} + \alpha_i^{**}Lnq_{t-1}^{usa} + \alpha_i^{**}Lnq_{t-1}^{row}, \quad (10)$$

$$\theta_{ij}\mu_{t-1} = \theta_{ij}\mu_{mext-1} + \theta_{ij}\mu_{usat-1} + \theta_{ij}\mu_{rowt-1} = \theta_{ij}Lnq_{t-1}^{mex} + \theta_{ij}Lnq_{t-1}^{usa} + \theta_{ij}Lnq_{t-1}^{row}, \text{ and} \quad (11)$$

$$\eta_i\mu_{t-1} = \eta_i\mu_{mext-1} + \eta_i\mu_{usat-1} + \eta_i\mu_{rowt-1} = \eta_i Lnq_{t-1}^{mex} + \eta_i Lnq_{t-1}^{usa} + \eta_i Lnq_{t-1}^{row}. \quad (12)$$

The specification proposed consumes more degrees of freedom than the H&G model. Thus, it will not be a good model for short period data. However, for monthly or weekly expenditure data this approach could be better than H&G's.

To obtain the dynamic model with linear habit formation (2) from the SR-D-IAIDS with own- and cross-habit formation (6), the habit terms $[\theta_{ijj_{t-1}}, \eta_{ij}]$ need to be set to zero.

The theoretical restrictions for the SR-D-IAIDS model with own- and cross-habit formation (6) are as follows:

- Adding up: $\sum_i \alpha_i^* = 1, \sum_i \sum_j \alpha_{ij}^{**} = 0, \sum_i \gamma_{ij} = \sum_i \theta_{ijj_{t-1}} = 0, \sum_i \beta_i = \sum_i \eta_{ij} = 0$;
- Homogeneity: $\sum_j \gamma_{ij} = \sum_j \theta_{ijj_{t-1}} = 0$; and
- Symmetry: $\gamma_{ij} = \gamma_{ji}, \theta_{ijj_{t-1}} = \theta_{jij_{t-1}}$.

Notice that the restrictions imposed are very similar to H&G's, except the adding up restriction "$\sum_i \sum_j \alpha_{ij}^{**} = 0$." For the latter, this approach assumes adding up at the aggregated level, and not at the good-specific level. The intuition for imposing the restriction is to allow the aggregated term $[\sum_j \alpha_{ij}^{**}]$ to be equivalent to the term $[\alpha_i^{**}]$ in the H&G model. Notice that their restriction $[\sum_i \alpha_i^{**} = 0]$ is equivalent to the proposed restriction $[\sum_i \sum_j \alpha_{ij}^{**} = 0]$. All this implies that the linear habit effect will be sensitive to the eliminated equation, but at the aggregated level, the habit effects should be the same irrespective of the equation dropped. As stated in the linear specification, the fully restricted dynamic model (with the restriction $\sum_i \alpha_{ij}^{**} = 0$) is compared with the proposed model (with the restriction $\sum_i \sum_j \alpha_{ij}^{**} = 0$).

2.3 Long-Run Dynamic Specification with Behavioral Habit Formation

So far, the above dynamic IAIDS models assume that habit-forming behaviors depend only on short memory. However, it could be the case that distant past consumption affects the current consumption allocation. This is especially true for the bell pepper industry because, in the decade of the 90s, the U.S. consumers were used to the scarcity of this product during the months of winter and spring. But, because of supply increases from Mexico and the ROWs, they eventually

changed their purchasing behavior. Therefore, their buying habits for bell pepper have changed through time.

The intuition behind introducing a "long memory" effect to the consumer habit formation is based on the idea that all past consumptions influence today's consumption allocation, but that influence differs through time because the consumer remembers more easily the most recent past consumption than the more distant ones.

To introduce that idea into the IAIDS model, H&G made the IAIDS depends on a geometrically weighted average of the entire history of all past consumption levels of each good. Thus, this method will create a stock of habit formation effects that in each period will condition the typical consumer's allocation decisions. Embedding this term to the previous SR-D-NL/ IAIDS model will generate a dynamic specification that depends on both recent and distant consumption histories.

The challenging portion to specify the LR-D-IAIDS with long memory habit formation is the introduction of the "geometrically weighted average past consumptions of good j_{th}" in the IAIDS. To achieve this, they defined:

$$\tilde{\mu}_{t-1} = \sum_{j=1}^{n} \tilde{\mu}_{jt-1} \tag{13}$$

where: $\tilde{\mu}_{jt-1} = lnq_{jt-1} + (1 - \phi_j)\tilde{\mu}_{jt-2}, \quad for\ j = 1, .., n.$

To simulate the "geometrically weighted average past consumptions of good i_{th}" H&G had to borrow from Wold (1954). Thus, he expressed the term $\tilde{\mu}_{jt-1}$ as a *distributed lag function* of the natural logarithm of all past consumption levels of the j_{th} good as follows:

$$\tilde{\mu}_{jt-1} = \sum_{\tau=0}^{\tau=m} \delta_j^{\tau} lnq_{jt-\tau-1} \tag{14}$$

where

- $\tilde{\mu}_{jt-1}$ is a habit variable, which condenses the habit effects of the past consumption for a particular commodity (e.g., local bell pepper consumption during four periods).
- ϕ_j is the depreciation rate of the existing stock (state) of habit effects for the j_{th} good at the end of period *t-1*.
- $\tilde{\mu}_{t-1}$ is the sum of all individual stock effects. Notice that this term is the equivalent to μ_{t-1} from the SR-D-IAIDS model.

Notice that if $\tau = 0$, the term then $\tilde{\mu}_{t-1}$ becomes μ_{t-1} of the SR-D-IAIDS model.

Expanding equation 14, yields:

$$\tilde{\mu}_{jt-1} = lnq_{jt-1} + \delta_j^1 lnq_{jt-2} + \delta_j^2 lnq_{jt-3} + \cdots + \delta_j^{\infty} lnq_{jt-m-1}.$$

Combining equation 13 and 14, and expanding it, yields:

$$\tilde{\mu}_{t-1} = \sum_{j=1}^{n}[lnq_{jt-1} + \delta_j^1 lnq_{jt-2} + \delta_j^2 lnq_{jt-3} + \cdots + \delta_j^m lnq_{jt-m-1}].$$

Expanding it for the case of bell pepper, yields:

$$\tilde{\mu}_{t-1} = \tilde{\mu}_{1t-1} + \tilde{\mu}_{2t-1} + \tilde{\mu}_{3t-1} = \begin{bmatrix} lnq_{1_{t-1}} + \ \delta_1^1 lnq_{1_{t-2}} + \delta_1^2 lnq_{1_{t-3}} + \cdots + \ \delta_1^m lnq_{1_{t-m-1}} + \\ lnq_{2_{t-1}} + \ \delta_2^1 lnq_{2_{t-2}} + \delta_2^2 lnq_{2t-3} + \cdots + \ \delta_2^m lnq_{2_{t-m-1}} + \\ lnq_{3_{t-1}} + \ \delta_3^1 lnq_{3_{t-2}} + \delta_3^2 lnq_{3_{t-3}} + \cdots + \ \delta_3^m lnq_{3_{t-m-1}} \end{bmatrix}, \quad (15)$$

where Mex=1, USA=2, and ROW=3.

Holt and Goodwin (1997) augmented the term $\tilde{\mu}_{t-1}$ (15) into the utility distance function, as done in the SR-D-IAIDS model, from which they derived the dynamic budget share equations with long-memory habit formation effects. The H&G LR-D-IAIDS is as follows:

$$w_{it} = \alpha_i^* + \alpha_i^{**}\tilde{\mu}_{t-1} + \sum_j(\gamma_{ij} + \theta_{ij}\tilde{\mu}_{t-1})Lnq_j + \ (\beta_i + \eta_i\tilde{\mu}_{t-1})Ln\tilde{Q}_t^* \quad (16)$$

where

$$Ln\tilde{Q}_t^* = \alpha_0 + \sum_j(\alpha_j^* + \alpha_j^{**}\tilde{\mu}_{t-1})Lnq_j + \frac{1}{2}\sum_i\sum_j(\gamma_{ij} + \theta_{ij}\tilde{\mu}_{t-1})Lnq_iLnq_j.$$

Notice that H&G assumed that the individual stock of habits $\tilde{\mu}_{jt-1}$ affects the expenditure share equations in the same magnitude (see equations 15 and 16). For example, the accumulated habits of consuming the Mexican bell pepper has the same effect on the market share of the U.S. bell pepper, as would the accumulated habits of consuming the locally produced bell pepper. More explicitly, their assumption implies the following for the bell pepper empirical application:

$$\alpha_i^{**}\tilde{\mu}_{t-1} = \alpha_i^{**}\tilde{\mu}_{mext-1} + \alpha_i^{**}\tilde{\mu}_{usat-1} + \alpha_i^{**}\tilde{\mu}_{rowt-1},$$

$$\theta_{ij}\tilde{\mu}_{t-1} \quad = \theta_{ij}\tilde{\mu}_{mext-1} + \theta_{ij}\tilde{\mu}_{usat-1} + \theta_{ij}\tilde{\mu}_{rowt-1}, \text{ and}$$

$$\eta_i\tilde{\mu}_{t-1} \quad = \eta_i\tilde{\mu}_{mext-1} + \eta_i\tilde{\mu}_{usat-1} + \eta_i\tilde{\mu}_{rowt-1}.$$

The H&G LR-D-IAIDS model (equation 16) has nested within its specification the SR-D-IAIDS model (4). Thus, imposing the restriction $\delta_i = 0\ \forall i\ \&\ j$ yields the SR-D-IAIDS model. Holt and Goodwin (1997) imposed homogeneity, symmetric and adding up conditions identical to the SR-D-IAIDS, which guarantees integrability.

Even though H&G LR-D-IAIDS model is a proven, general, and flexible specification of habit formation in the inverse demand system, it can be even more flexible if the stock of own- and cross-habits is allowed to affect the market share in different magnitudes. Thus, following the same approach used to derived equation (6), this study proposes a LR-D-IAIDS model with own- and cross-habit formation, which has the following form:

$$w_i = \alpha_i^* + \sum_j \alpha_{ij}^{**}\tilde{\mu}_{j_{t-1}}^* + \sum_j(\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}}\tilde{\mu}_{j_{t-1}}^*)Lnq_j + (\beta_i + \sum_j \eta_{ij}\tilde{\mu}_{j_{t-1}}^*)Ln\ddot{Q}_t^* \quad (17)$$

Where, $Ln\ddot{Q}_t^* = \alpha_0 + \sum_j(\alpha_j^* + \sum_j \alpha_{ij}^{**}\tilde{\mu}_{j_{t-1}}^*)Lnq_j + \frac{1}{2}\sum_i\sum_j(\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}}\tilde{\mu}_{j_{t-1}}^*)Lnq_iLnq_j$.

Notice that this specification allows the stock of own- and cross-consumption habits to affect the expenditure share equations in different magnitudes, which is very similar to SR-D-IAIDS specification with specific habit formation (see eq. 6, 7, 8, and 9). Thus, this model is potentially more flexible than the H&G LR-D-IAIDS model.

The proposed LR-D-IAIDS model (eq. 17) yields the short-run version (eq. 6) by imposing the restriction $\delta_i = 0\ \forall i\ \&\ j$. Thus, the long and short run dynamic version share the same adding up, homogeneity, and symmetry restrictions.

Likewise, the same dynamic restriction imposed in (eq. 6), will reduce the proposed LR-D-IAIDS model to the H&G long-run model. More explicitly:

$\alpha_{i1}^{**} = \alpha_{i2}^{**} = \cdots = \alpha_{in}^{**}$,

$\theta_{ij1_{t-1}} = \theta_{ij2_{t-1}} = \cdots = \theta_{ijn_{t-1}}$, and

$\eta_{i1} = \eta_{i2} = \cdots = \eta_{in}$.

2.4 Deriving the Dynamic Own- and Cross-Price Flexibilities

The general formula for the own- and cross-price flexibilities is as follows:

$$f_{ij} = \frac{\%\Delta \mathrm{p}_i}{\%\Delta \mathrm{q}_j} = -\delta_{ij} + \frac{\partial w_i}{\partial lnq_j}\text{; where } \delta_{ij} = \begin{bmatrix} 1, & if\ j = i \\ 0, & if\ j \neq i \end{bmatrix}, \tag{18}$$

due to the following identity[3]:

$$\frac{\partial w_i}{\partial lnq_j} = \frac{\partial}{\partial lnq_j}\frac{p_i q_i}{\mathrm{E}} = \frac{\partial p_i}{\partial lnq_j}\frac{q_i}{\mathrm{E}} = \frac{\partial p_i}{\partial lnq_j}\frac{p_i q_i}{p_i \mathrm{E}} = \frac{\partial lnp_i}{\partial lnq_j}\frac{p_i q_i}{\mathrm{E}} = \frac{\%\Delta p_i}{\%\Delta q_j} w_i = f'_{ij} w_i,$$

Thus, $f'_{ij} = \left(\frac{1}{w_i}\right)\frac{\partial w_i}{\partial lnq_j}$. Therefore, equation (18) becomes:

$$f_{ij} = \frac{\%\Delta \mathrm{p}_i}{\%\Delta \mathrm{q}_j} = -\delta_{ij} + \left(\frac{1}{w_i}\right)\frac{\partial w_i}{\partial lnq_j}. \tag{19}$$

Applying the equation (19) to the H&G D-IAIDS models (equations 1, 4, and 16) yield:

$$f_{ij}^{l} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} + \frac{\beta_i}{w_i} * \frac{\partial LnQ}{\partial lnq_j},$$

$$f_{ij}^{SR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \theta_{ij}\mu_{t-1}}{w_i}\right) + \left(\frac{\beta_i + \eta_i \mu_{t-1}}{w_i}\right) * \frac{\partial LnQ_t^*}{\partial lnq_j}, \text{ and}$$

3 where E is total expenditure

$$f_{ij}^{LR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \theta_{ij}\tilde{\mu}_{t-1}}{w_i}\right) + \left(\frac{\beta_i + \eta_i\tilde{\mu}_{t-1}}{w_i}\right) * \frac{\partial Ln\tilde{Q}_t^*}{\partial lnq_j}.$$

Applying the equation (19) to the proposed D-IAIDS models (equations 2, 5, and 17), which are conditioned to own- and cross-habit formation, yield:

$$f_{ij}^{\prime l} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} + \frac{\beta_i}{w_i} * \frac{\partial Ln\tilde{Q}}{\partial lnq_j},$$

[4] $f_{ij}^{\prime SR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \mu_{jt-1}}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij} \mu_{jt-1}}{w_i}\right) * \frac{\partial Ln\breve{Q}_t^*}{\partial lnq_j}$, and

$$f_{ij}^{\prime LR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \tilde{\mu}_{j_{t-1}}^*}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij} \tilde{\mu}_{j_{t-1}}^*}{w_i}\right) * \frac{\partial Ln\ddot{Q}_t^*}{\partial lnq_j}.$$

Solving for the term $\partial LnQ\ /\partial lnq_j$ in each of the previous equation, the uncompensated price flexibilities become:

$$f_{ij}^{l} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} + \frac{\beta_i}{w_i}\left(\alpha_j^* + \alpha_j^{**}\mu_{t-1} + \sum_i \gamma_{ij} Lnq_i\right) \tag{20}$$

$$f_{ij}^{\prime l} = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} + \frac{\beta_i}{w_i}\left(\alpha_j^* + \sum_j \alpha_{ij}^{**} Lnq_{jt-1} + \sum_i \gamma_{ij} Lnq_i\right) \tag{21}$$

$$f_{ij}^{SR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \theta_{ij}\mu_{t-1}}{w_i}\right) + \left(\frac{\beta_i + \eta_i\mu_{t-1}}{w_i}\right)\left(\alpha_j^* + \alpha_j^{**}\mu_{t-1} + \sum_i(\gamma_{ij} + \theta_{ij}\mu_{t-1})Lnq_i\right) \tag{22}$$

$$f_{ij}^{\prime SR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \mu_{j_{t-1}}}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij} \mu_{j_{t-1}}}{w_i}\right) *$$

$$\left\{\alpha_j^* + \sum_j \alpha_{ij}^{**} \mu_{j_{t-1}} + \sum_i(\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \mu_{j_{t-1}})Lnq_{it}\right\} \tag{23}$$

$$f_{ij}^{LR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \theta_{ij}\tilde{\mu}_{t-1}}{w_i}\right) + \left(\frac{\beta_i + \eta_i\tilde{\mu}_{t-1}}{w_i}\right)\left(\alpha_j^* + \alpha_j^{**}\tilde{\mu}_{t-1} + \sum_i(\gamma_{ij} + \theta_{ij}\tilde{\mu}_{t-1})Lnq_i\right) \tag{24}$$

[4] Recall that for the proposed SR-D- IAIDS model: $\mu_{jt-1} = Lnq_{j_{t-1}}$

$$f_{ij}'^{LR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \tilde{\mu}^*_{j_{t-1}}}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij} \tilde{\mu}^*_{j_{t-1}}}{w_i}\right) *$$

$$\{\alpha_j^* + \sum_j \alpha_{ij}^{**} \tilde{\mu}^*_{j_{t-1}} + \sum_i (\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \tilde{\mu}^*_{j_{t-1}}) Lnq_i\}. \quad (25)$$

The above derived price flexibilities have too many parameters due to the term α_j^*, which complicates their computation. Recall that:

$$a_j^* = a_j + \delta_{j1} D^{jan} + \delta_{j2} D^{feb} + \cdots + \delta_{j11} D^{fall} + + \delta_{j12} * trend$$

Thus, equations 20, 21, 22, , 24, and 25 are simplified by substituting the $\partial LnQ \ / \partial lnq_j$ by the following identities:

$$\frac{\partial LnQ_t}{\partial lnq_j} = \left(\alpha_j^* + \alpha_j^{**} \mu_{t-1} + \sum_i \gamma_{ij} Lnq_i\right) = \qquad \{w_j - \beta_j lnQ_t\}$$

$$\frac{\partial Ln\tilde{Q}_t}{\partial lnq_j} = \left(\alpha_j^* + \sum_j \alpha_{ij}^{**} Lnq_{jt-1} + \sum_i \gamma_{ij} Lnq_i\right) = \qquad \{w_j - \beta_j ln\tilde{Q}_t\}$$

$$\frac{\partial LnQ_t^*}{\partial lnq_j} = \left(\alpha_j^* + \alpha_j^{**} \mu_{t-1} + \sum_i (\gamma_{ij} + \theta_{ij} \mu_{t-1}) Lnq_i\right) = \qquad \left\{w_j - (\beta_j + \eta_j \mu_{t-1}) LnQ_t^*\right\}$$

$$\frac{\partial Ln\breve{Q}_t^*}{\partial lnq_j} = \left\{\alpha_j^* + \sum_j \alpha_{ij}^{**} \mu_{j_{t-1}} + \sum_i \left(\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \mu_{j_{t-1}}\right) Lnq_i\right\} = \qquad \left\{w_j - \left(\beta_j + \sum_j \eta_{ji} \mu_{j_{t-1}}\right) Ln\breve{Q}_t^*\right\}$$

$$\frac{\partial Ln\tilde{Q}_t^*}{\partial lnq_j} = \left(\alpha_j^* + \alpha_j^{**} \tilde{\mu}_{t-1} + \sum_i (\gamma_{ij} + \theta_{ij} \tilde{\mu}_{t-1}) Lnq_i\right) = \qquad \left\{w_j - (\beta_j + \eta_j \tilde{\mu}_{t-1}) Ln\tilde{Q}_t^*\right\}$$

$$\frac{\partial Ln\ddot{Q}_t^*}{\partial lnq_j} = \left\{\alpha_j^* + \sum_j \alpha_{ij}^{**} \tilde{\mu}^*_{j_{t-1}} + \sum_i (\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \tilde{\mu}^*_{j_{t-1}}) Lnq_i\right\} = \qquad \left\{w_j - \left(\beta_j + \sum_j \eta_{ji} \tilde{\mu}^*_{j_{t-1}}\right) Ln\ddot{Q}_t^*\right\}$$

Thus, the simplified version of the dynamic price flexibilities are as follows:

$$f_{ij}^l = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} + \frac{\beta_i}{w_i}\{w_j - \beta_j lnQ_t\} \quad (26)$$

$$f_{ij}'^l = -\delta_{ij} + \frac{\gamma_{ij}}{w_i} + \frac{\beta_i}{w_i}\{w_j - \beta_j ln\tilde{Q}_t\} \quad (27)$$

$$f_{ij}^{SR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \theta_{ij} \mu_{t-1}}{w_i}\right) + \left(\frac{\beta_i + \eta_i \mu_{t-1}}{w_i}\right)\left\{w_j - \left(\beta_j + \eta_j \mu_{t-1}\right) LnQ_t^*\right\} \quad (28)$$

$$f_{ij}'^{SR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}} \mu_{j_{t-1}}}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij} \mu_{j_{t-1}}}{w_i}\right)\left\{w_j - \left(\beta_j + \sum_j \eta_{ji} \mu_{j_{t-1}}\right) Ln\breve{Q}_t^*\right\} \quad (29)$$

$$f_{ij}^{LR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \theta_{ij}\tilde{\mu}_{t-1}}{w_i}\right) + \left(\frac{\beta_i + \eta_i\tilde{\mu}_{t-1}}{w_i}\right) * \left\{w_j - \left(\beta_j + \eta_j\tilde{\mu}_{t-1}\right)Ln\tilde{Q}_t^*\right\} \quad (30)$$

$$f_{ij}'^{LR} = -\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ij j_{t-1}}\tilde{\mu}_{j_{t-1}}^*}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij}\tilde{\mu}_{j_{t-1}}^*}{w_i}\right)\left\{w_j - \left(\beta_j + \sum_j \eta_{ji}\tilde{\mu}_{j_{t-1}}^*\right)Ln\ddot{Q}_t^*\right\} \quad (31)$$

Equations 26, 27, 28, 29, 30, and 31 will be used to calculate the uncompensated price flexibilities. A common practice is to report the price flexibilities holding the expenditure share and the quantity index, and habit terms constant at the mean. Additional to the mean price flexibilities, this study will predict and graph the valued of each own- and cross-price flexibility during the period of 1998-2017 for the model with the best fit.

Notice that the H&G model price flexibilities (f_{ij}^{l}, f_{ij}^{SR}, & f_{ij}^{LR}) are different from the price flexibilities that consider own- and cross-habit formation ($f_{ij}'^{l}, f_{ij}'^{SR}$, & $f_{ij}'^{LR}$). The price flexibilities of the models with linear habit formation differs in the quantity index as do the SR and LR models. However, the differences are more striking for the models with short and long memory habits formation.

Notice from equations 28 and 29 that the aggregated consumption habits of the previous period affect the magnitude of the short run price flexibilities. However, the $f_{ij}'^{SR}$ allows the own- and cross-consumption habit of the previous period to have differentiated effect. Thus, the proposed model allows the magnitude of the flexibilities to vary due to the specific lag consumption effect of each of the goods *j* and not only at the aggregate level [$\sum_{j_{t-1}} \theta_{ij j_{t-1}}\tilde{\mu}_{j_{t-1}}^*$ & $\sum_j \eta_{ij}\tilde{\mu}_{j_{t-1}}^*$].

Notice from equations 30 and 31 that the magnitude of the LR-price flexibilities are conditioned by the historical aggregated consumption habits as presented in equation (15). However, the $f_{ij}'^{LR}$ allows the current and distant specific consumption habits to affect the price flexibilities differently [$\sum_{j_{t-1}} \theta_{ij j_{t-1}}\tilde{\mu}_{j_{t-1}}^*$, $\sum_j \eta_{ij}\tilde{\mu}_{j_{t-1}}^*$], whereas H&G price flexibilities assume

the same impact across goods [$\theta_{ij}\tilde{\mu}_{t-1}$, $\eta_i\tilde{\mu}_{t-1}$]. In this empirical case, it means that the historical habits of purchasing bell pepper produced in Mexico will have a different impact on the price flexibilities than the historical habits of purchasing bell pepper produced locally. This contrasts with H&G approach because they assume that the historical habits of purchasing from both sources affect the price flexibilities in the same way.

2.5 Deriving the Own- and Cross-Habit Flexibilities

The dynamic specifications allow the evaluation of how changes in consumption habits affect the price flexibilities. This would be valuable information for stakeholders in the entire value chain, either for policy-making or for opportunistic decisions. Changes in consumption habits could increase or decrease the price response of a commodity to changes in quantity supplied. Thus, policy makers and intermediaries can act accordingly with such information.

Given that the price flexibilities obtained from H&G model and the proposed dynamic model are conditioned to habit formation, *habit flexibilities*[5] can be derived, which are defined as how much the current price flexibility change in response to small changes in the consumption habits. Thus, the derivative of the uncompensated price flexibilities (equations 26, 27, 28, 29, 30, and 31) with respect to changes in consumption habits are as follows:

$$\frac{\partial f_{ij}^{l}}{\partial \mu_{t-1}} = \frac{\beta_i}{w_i} * \{\alpha_j^{**}\} \tag{32}$$

$$\frac{\partial f_{ij}^{\prime l}}{\partial \mu_{t-1}} = \frac{\beta_i}{w_i} * \{\alpha_{ij}^{**}\} \tag{33}$$

$$\frac{\partial f_{ij}^{SR}}{\partial \mu_{t-1}} = \frac{\theta_{ij}}{w_i} + \frac{\eta_i}{w_i}\{w_j - (\beta_j + \eta_j\mu_{t-1})LnQ_t^*\} + \left(\frac{\beta_i+\eta_i\mu_{t-1}}{w_i}\right) * \left\{\frac{\partial LnQ_t^*}{\partial lnq_j}/\partial\mu_{t-1}\right\} \tag{34}$$

5 Holt & Goodwin (1997) defined the habit flexibilities as a percentage change in the ith price due to 1% increase in the jth habit term. However, since all lag quantity share the same habit coefficient (θ_{ij}, η_i), a more appropriate definition for their habit flexibilities is a percentage change on the ith price due to 1% increase in the aggregated habit term (μ_{t-1}).

$$\frac{\partial f_{ij}^{\prime SR}}{\partial \mu_{j_{t-1}}} = \frac{\theta_{ijj_{t-1}}}{w_i} + \frac{\eta_{ij}}{w_i}\left\{w_j - \left(\beta_j + \sum_j \eta_{ij}\mu_{j_{t-1}}\right)Ln\breve{Q}_t^*\right\} + \left(\frac{\beta_i + \sum_j \eta_{ij}\mu_{j_{t-1}}}{w_i}\right)\left\{\frac{\partial Ln\breve{Q}_t^*}{\partial lnq_j} / \partial \mu_{j_{t-1}}\right\} \quad (35)$$

$$\frac{\partial f_{ij}^{LR}}{\partial \tilde{\mu}_{t-1}} = \frac{\theta_{ij}}{w_i} + \frac{\eta_i}{w_i}\left\{w_j - \left(\beta_j + \eta_i\tilde{\mu}_{t-1}\right)Ln\tilde{Q}_t^*\right\} + \left(\frac{\beta_i + \eta_i\tilde{\mu}_{t-1}}{w_i}\right) * \left\{\frac{\partial Ln\tilde{Q}_t^*}{\partial lnq_j} / \partial \tilde{\mu}_{t-1}\right\} \quad (36)$$

$$\frac{\partial f_{ij}^{\prime LR}}{\partial \tilde{\mu}_{j_{t-1}}^*} = \frac{\theta_{ijj_{t-1}}}{w_i} + \frac{\eta_{ij}}{w_i}\left\{w_j - \left(\beta_j + \sum_j \eta_{ij}\tilde{\mu}_{j_{t-1}}^*\right)Ln\ddot{Q}_t^*\right\} + \left(\frac{\beta_i + \sum_j \eta_{ij}\tilde{\mu}_{j_{t-1}}^*}{w_i}\right)\left\{\frac{\partial Ln\ddot{Q}_t^*}{\partial lnq_j} / \partial \tilde{\mu}_{j_{t-1}}^*\right\} \quad (37)$$

Equations 32-37 will be used to calculate the uncompensated habit flexibilities holding the expenditure share and the quantity index constant at the mean.

Notice that in H&G model, habit flexibilities ($h_{ij}^{l}, h_{ij}^{SR}, and\ h_{ij}^{LR}$) are different from the habit flexibilities ($h_{ij}^{\prime l}, h_{ij}^{\prime SR}, and\ h_{ij}^{\prime LR}$) derived from the proposed model. The proposed habit flexibilities ($h_{ij}^{\prime l}, h_{ij}^{\prime SR}, and\ h_{ij}^{\prime LR}$) allow the price flexibilities to change in response to changes in own- and cross-habit formation. This contrast with Holt and Goodwin (1997) since their model yields the same habit flexibilities at the specific and aggregated level.

The aforementioned statement is visualized clearly by comparing the habit flexibilities (32, 33) derived from the D-IAIDS model with linear habits formation. The $\partial f_{ij}^{l} / \partial \mu_{jt-1}$ will be the same irrespective of *j*. On the contrary, the $\partial f_{ij}^{\prime l} / \partial \mu_{jt-1}$ will vary according to changes in the purchasing habit from the source *j*.

For the short run and long run habit flexibilities, the aforementioned statement can be harder to visualize. However, further simplification for equations 34 and 36 indicate that their habit flexibilities ($h_{ij}^{SR}, and\ h_{ij}^{LR}$) are the same across j. This indicates, that the H&G model assumes that changes in habit at the aggregated level and at the specific level affect the price flexibilities in the same magnitude. More explicitly, further simplification for equations 34 and 36 are as follows:

$\frac{\partial LnQ_t^*}{\partial lnq_j} / \partial \mu_{jt-1} = \left(\alpha_j^{**} + \sum_i \theta_{ij} Lnq_i\right)$, and

$\frac{\partial Ln\tilde{Q}_t^*}{\partial lnq_j} / \tilde{\mu}_{jt-1} = \left(\alpha_j^{**} + \sum_i \theta_{ij} Lnq_i\right)$.

For comparison purposes between the proposed specification and H&G model, the *SR and LR aggregated habit flexibilities* are estimated by adding up across j the respective own- and cross-habit flexibilities:

$$\frac{\partial f_{ij}'^{SR}}{\partial \mu_{jt-1}} = \sum_{j_{t-1}} \partial f_{ij}'^{SR} / \partial \mu_{jt-1} \; ; \; \frac{\partial f_{ij}'^{LR}}{\partial \tilde{\mu}_{t-1}^*} = \sum_{j_{t-1}} \partial f_{ij}'^{LR} / \partial \tilde{\mu}_{j_{t-1}}^*. \tag{38}$$

2.6 Deriving the Dynamic Scale Flexibilities

The scale flexibilities of the D-IAIDS models are obtained using the homogeneity aggregation relationship of the price flexibilities by adding up across *j*. For example, the LR scale flexibilities conditioned to own- and cross-habit formation are derived as follows:

$$f_i'^{LR} = \sum_j f_{ij}'^{LR},$$

$$= \sum_j \left[-\delta_{ij} + \left(\frac{\gamma_{ij} + \sum_{j_{t-1}} \theta_{ijj_{t-1}} \tilde{\mu}_{j_{t-1}}^*}{w_i}\right) + \left(\frac{\beta_i + \sum_j \eta_{ij} \tilde{\mu}_{j_{t-1}}^*}{w_i}\right)\left\{w_j - \left(\beta_j + \eta_j \sum_j \eta_{ij} \tilde{\mu}_{j_{t-1}}^*\right) Ln\tilde{Q}_t^*\right\}\right],$$

$$= \quad -1 \quad + \quad 0 \quad + \quad 0 \quad + \left(\frac{\beta_i + \sum_j \eta_{ij} \tilde{\mu}_{j_{t-1}}^*}{w_i}\right) * \left\{1 - \quad (0 + \quad 0 \quad) Ln\tilde{Q}_t^*\right\}.$$

Hence,

$$f_i'^{LR} = \sum_j f_{ij}'^{LR} = \quad -1 \quad + \left(\beta_i + \sum_j \eta_{ij} \tilde{\mu}_{j_{t-1}}^*\right)/w_i \tag{39}$$

Similarly, the other models scale flexibilities are as follows:

$$f_i^l = \sum_j f_{ij} = \quad -1 \quad + \beta_i / w_i, \tag{40}$$

$$f_i'^l = \sum_j f_{ij} = \quad -1 \quad + \beta_i / w_i, \tag{41}$$

$$f_i^{SR} = \sum_j f_{ij}^{SR} = \quad -1 \quad + (\beta_i + \eta_i \mu_{t-1})/w_i, \tag{42}$$

$$f_i'^{SR} = \sum_j f_{ij}'^{SR} = \quad -1 \quad + (\beta_i + \sum_j \eta_{ij} \mu_{t-1})/w_i, \text{ and} \tag{43}$$

$$f_i^{LR} = \sum_j f_{ij} \; = \quad -1 \; + (\beta_i + \eta_i \tilde{\mu}_{t-1})/w_i. \tag{44}$$

Notice that the short-run and the long-run scale price flexibilities (equations 39 and 43) in the proposed specification depend on the aggregate consumption habits $[\sum_j \eta_{ij}\mu_{t-1}, \sum_j \eta_{ij}\tilde{\mu}^*_{j_{t-1}}]$, but allowing differentiated habit effects in the scales flexibilities. On the contrary, H&G scale flexibilities are affected by all consumption habits in the same magnitude (η_i).

The compensated (i.e., Antonelli) price flexibilities is calculated using the following formula[6]:

$$f_{ij}^{comp} = f_{ij}^{uncomp} - w_j f_i. \tag{45}$$

3 The Bell Pepper Industry

Peppers are widely consumed vegetables in the United States, ranking among the top ten vegetables most purchased by consumers. There are numerous varieties of pepper consumed in the United States, which cannot be aggregated for demand estimation because they are too heterogeneous. Perhaps the pepper most commonly found in a typical household refrigerator is the "Bell Pepper", also called the sweet pepper. As shown in figure 1, its consumption has nearly doubled. Likewise, the nominal and real expenditure on bell pepper consumption has increased by a factor of three and two, respectively. This implies that the price of bell pepper has increased during the period 1998-2016, and its demand has increased faster than supply. Furthermore, that increase in price could be explained by the increase in supply of high quality colored bell pepper produced in greenhouses. In the last two decades, Mexico and the United States have significantly increased the production area using greenhouses, while the ROW (Netherlands,

[6] Barter & Bettendorf (1989) explained that most of the time the compensated cross-price flexibilities are positive for the following reasons: (1) the adding up condition forces the Antonelli matrix (compensated price effects) to be of rank (n-1); (2) a necessary condition for the distance function is to be quasi-concave; (3) Compensated inverse demand curves must slope downward. Thus, the restriction imposed to achieve those condition yields mostly (+) compensated cross-price flexibilities.

Spain, Israel, Canada, Central-America, Dominican Republic, etc.) supply bell peppers that are mainly produced under specialized greenhouses.

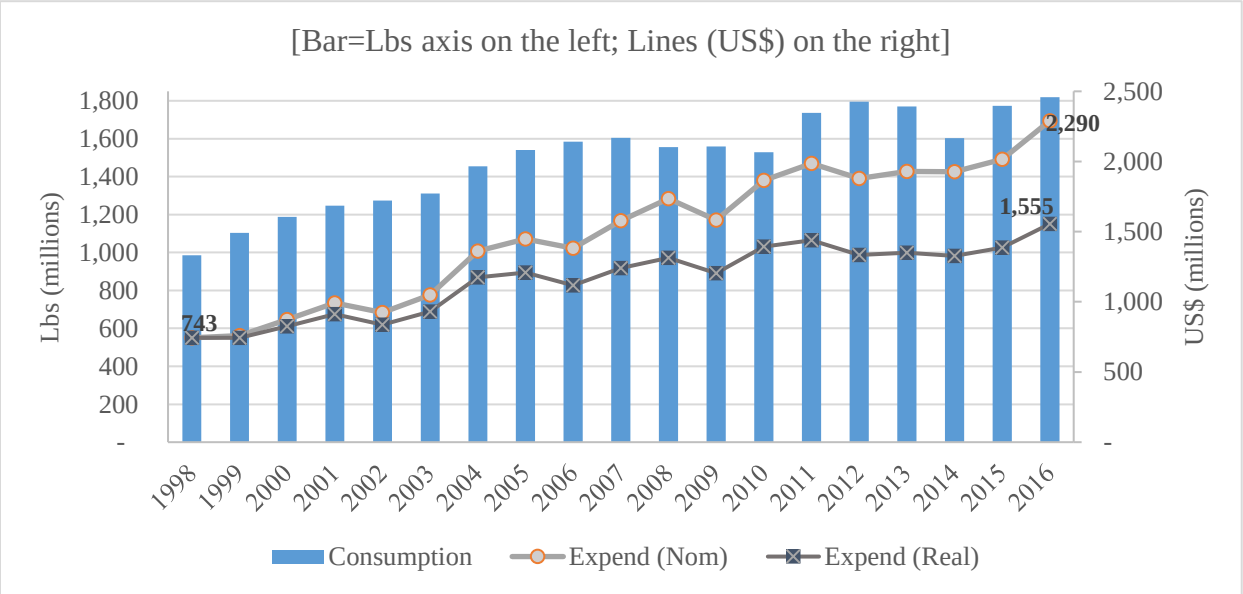


Figure 1. Total consumption and expenditure of fresh bell pepper in the United States

Although the United States has increased its supply of fresh bell pepper, it has not been enough to compensate for the increase in demand. As shown in figure 2, the U.S. consumer expenditure on locally produced bell pepper has decreased from 65% in 1998 to only 37% in 2016, while Mexico and the ROW have doubled their participation.

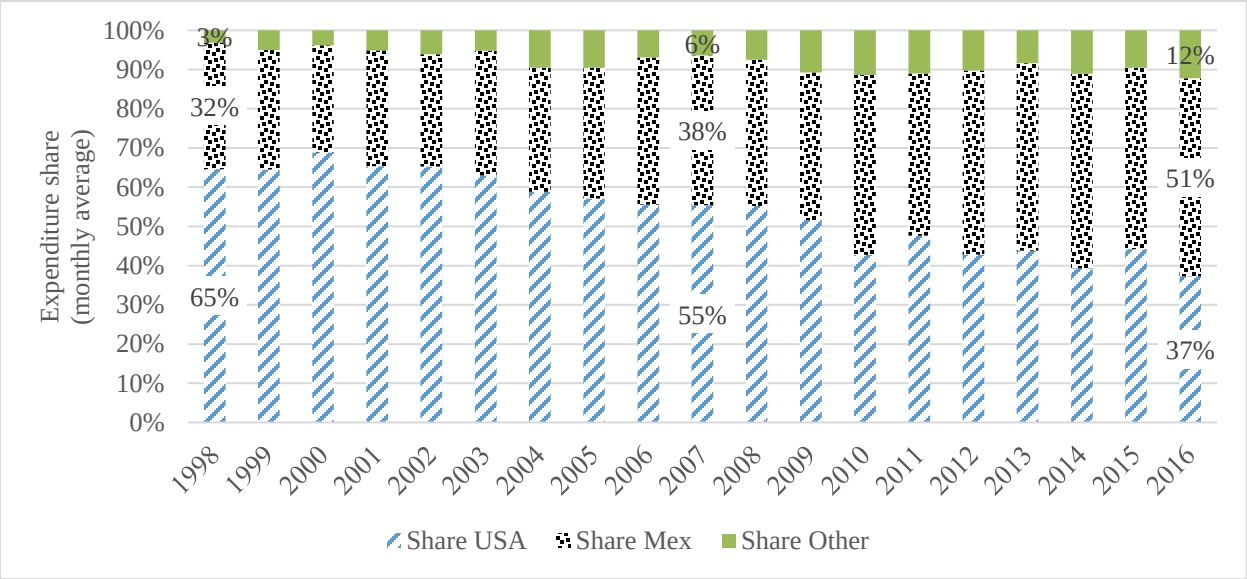


Figure 2. Budget allocation in the United States for fresh bell pepper by source

As shown in figure 3, per capita consumption was increasing steadily from 1998 to 2007, while both suppliers (United States and Mexico) were increasing supply. However, Mexican supply grew faster than U.S. supply, especially during the seasons of higher consumption in the United States (Nov-May) as shown in figure 4. Thus, the U.S. producers lost market share in this period because Mexican producers increased supply faster. One could argue that in the winter-spring period the substitution was mainly because of the increased availability of Mexican bell pepper. Notice that from 2008 to 2016, there is not any apparent increase in consumption per capita of bell pepper. Therefore, the U.S. producers lost market share during this period mainly because of substitution due to competition, while before that it was due to availability. Thus, it appears that U.S. consumers have substituted U.S. bell pepper with imported bell pepper.

The U.S. budget allocation for bell pepper imported from the ROW has increased significantly, from 3% to 12% share, during the period 1998-2016. The main reason for that increase is because its price is higher than the U.S. and Mexico bell pepper (figure 5). Thus, small increases in quantity from tropical and non-tropical countries increase its value to a level greater than the equivalent of U.S. or Mexican bell pepper. On the other hand, U.S. market share has fallen drastically because its price is the lowest of all the sources.

There are many factors that explain the differential in prices, but the environments of production are the most crucial ones. Bell pepper produced in a protected environment (e.g., greenhouse, shade-house) is considered of superior quality compared to bell pepper produced in open field (Gruda, 2005; Jovicich et al., 2004). The U.S. farmers, traditionally, have produced bell pepper in open field, while Mexico farmers produce almost all its bell pepper under greenhouse and shade-house conditions. Furthermore, Non-Tropical countries like the

Netherland, Spain, Israel, and Canada have the most advanced greenhouse technology, and their product is perceived of superior quality.

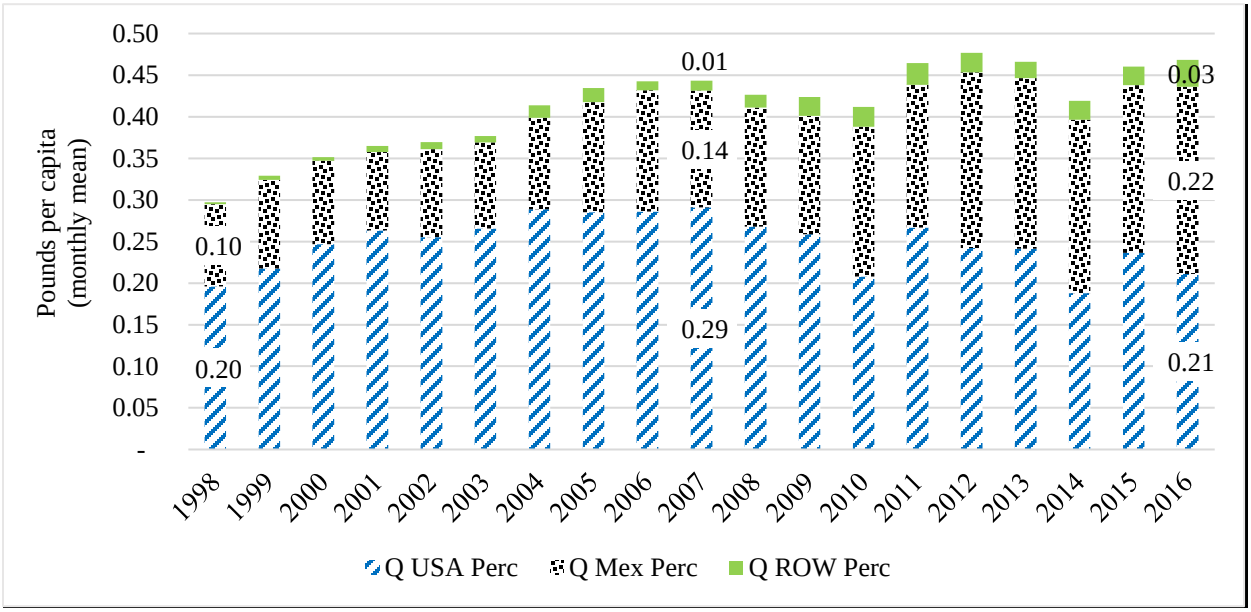


Figure 3. Per capita consumption of bell pepper in the United States by source and year

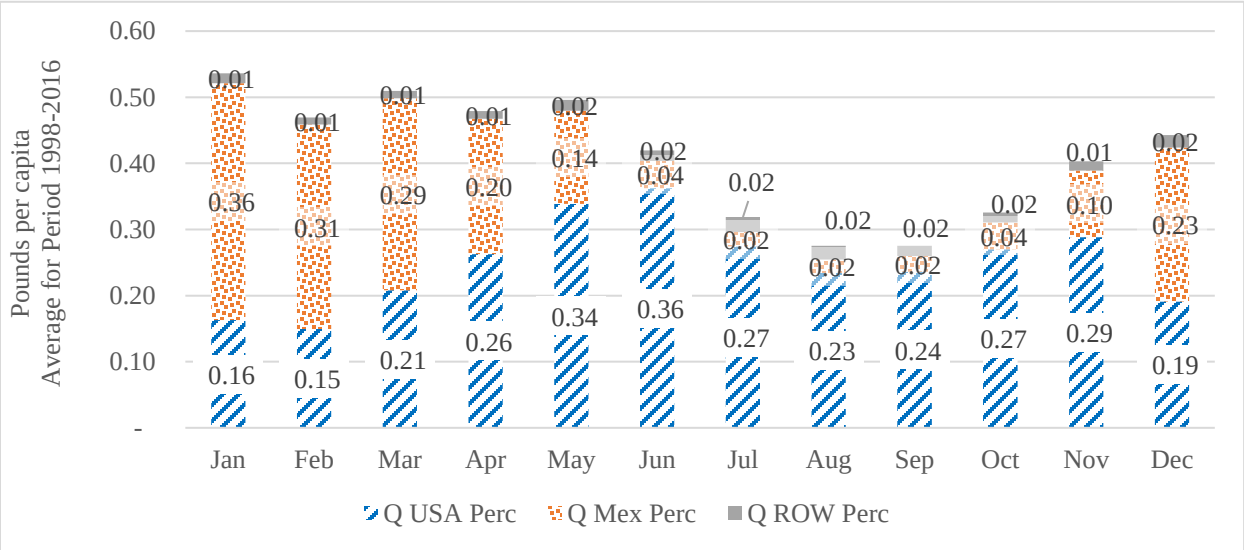


Figure 4. Per capita consumption of bell pepper in the United States by source and month

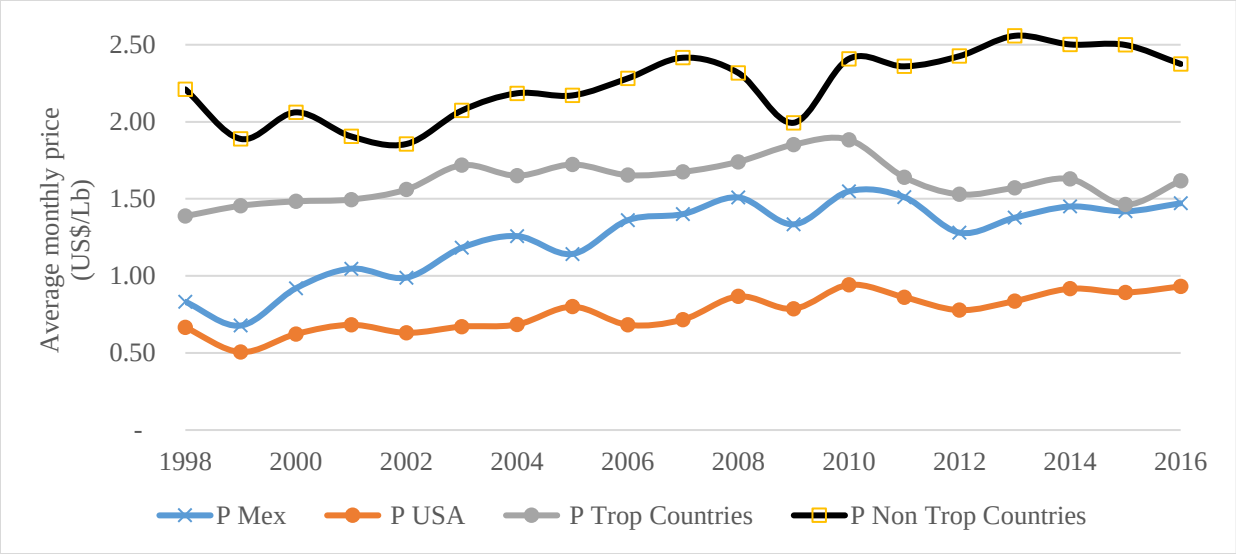


Figure 5. Price of fresh bell pepper by source in the United States, 1998-2016

4 Problem Statement

The increase in market share of Mexican's produce has created trade disputes between U.S. and Mexican producers in the past (Gunter and Ames, 1997). Also, the Donald J. Trump's administration has made comments to renegotiate the trade agreement with Mexico (Malkin, 2017). Therefore, it has become relevant to study the degree of substitution between U.S. and Mexican bell pepper to support the possibility of a new trade dispute or renegotiation of the bell pepper trade under NAFTA.

If the degree of substitution is high, and there is evidence of dumping, it might justify the imposition of a tariff on the imports of bell pepper from Mexico. But, a prerequisite of an anti-dumping dispute requires the evaluation of "product likeness", which can be studied by determining the degree of substitution as demonstrated by Grant, et al. (2010).

The USITC[7] is the institution responsible for the identification of "product likeness" or evaluating if the imported and domestic products are alike in all respects (Estes, 2003). The

[7] United States International Trade Commission

USITC bases its analysis on subjective assessments using industry characteristics, such as common production facilities, production process, employee characteristics, producer and consumer perception, distribution channels, and product interchangeability. VanSickle, et al. (1994) and Grant, et al. (2010) argued that because the USITC approach is subjective, the knowledge of "the degree of substitution" should increase the objectivity of defining "product likeness".

5 Justification and Benefits of this Study

Some researchers have quantified own elasticities for peppers, and its cross-elasticity with other vegetables such as onion, lettuce, and tomatoes (Naanwaab and Yeboah, 2012). However, none has quantified own and cross flexibilities by the source of production or by the color of bell pepper. Although it has been demonstrated that habit formation plays an important role in the magnitude of substitution possibilities (Holt and Goodwin, 1997; Ray, 1983), the effect of consumption habits on the bell pepper demand has not been studied. Furthermore, Holt and Goodwin (1997) and Ray (1983) assume that changes in the aggregated and commodity-specific stock of habits have the same effect on the substitution possibilities, which is a limitation of their approaches. Thus, a more flexible model is required to capture the effect of own- and cross-habit changes on the demand for bell pepper. Stakeholders, in the entire value chain of bell pepper, frequently make decisions blindly due to the lack of information on the behavior of supply and demand of bell pepper, thus this study will provide valuable information to better the understanding of the role of seasonality, and habit formation on the substitution possibilities between the sources of bell pepper in the United States market. Also, policymakers could use such information to aid the industry. Similarly, decision makers could use such information to make opportunistic choices. Researchers of the demand estimation for fruit and vegetables could

benefit from a novel approach to capture the effect of own- and cross-habit formation on the price flexibilities.

6 Data Description

Weekly data of fresh bell pepper are obtained from the AMS/USDA website[8]. Two data sets were extracted from the website (quantity and price) for the period 1998-2017. Weekly quantities entering the U.S. market from each country and local producer are recorded by the AMS/USDA.

Both data sets were merged by source and date. In the merging process, missing observations[9] of prices were obtained, which were predicted using a regression approach. Monthly values (price*quantity) and quantity consumed of fresh bell pepper were aggregated by three sources (United States, Mexico, and ROW). Monthly per-capita consumption was calculated using population data from the United States Census bureau[10]. In total, 240 monthly observations per equation were constructed to estimate the demand system. Weekly prices from each country[11] are at the wholesale level (terminal market). The AMS/USDA records prices for bell pepper in US$/container, which for this study needed to be transformed to US$/pound by using the following conversion values:

Presentation in volume	Weight** (Lb.)/pack	Presentation in volume	Weight (Lb.)/pack
1 1/4 bushel cartons	28.1	bushel baskets/cartons/crates	25.0
1 1/9 bushel (Several)	25.0	bushel cartons	25.0
1/2 bushel cartons (Several)	11.3	bushel crates	25.0
10 kg containers	22.0	cartons	25.0
3/4 bushel cartons	16.9	cartons 2 layer	25.0
6/10 bushel cartons	13.5	flat cartons	11.0
6/7 bushel cartons	19.3	Others	15.0
bushel baskets	25.0		

*Presentations of containers with weight values were excluded from this table.
**The weight estimates were obtained by talking to intermediaries, packinghouse and warehouse employees.

[8] https://marketnews.usda.gov/mnp/fv-report-config-step1?type=termPrice.
[9] Only 0.3% of the quantity data had missing prices.
[10] http://www.census.gov/topics/population.html.
[11] For the United States, price of bell pepper in each state were considered.

7 Empirical Approach and Treatment of Autocorrelation

Maximum likelihood estimation procedure will be used to estimate the dynamic inverse AIDS model. Since monthly data is used in this study, autocorrelation is likely to be detected in the equations' residuals. In order to detect serial correlation, the Durbin-Watson test will be used. The problem of controlling for serial correlation in a singular equations system is that the autoregressive estimates are no invariant to the deleted equation (Berndt and Savin, 1975). But from a practical standpoint, that does not generate an empirical problem since the parameter coefficients of interest remain invariant to the equation dropped. The typical approach address serial correlation in system of equation is by specifying a first autocorrelation [AR(1)] process in the n-equation share system. They are several tactics to specify the autoregressive matrix. In this study we follow Anderson and Blundell (1982), which require the estimation of $(n\text{-}1)^2$ autoregressive parameters.

In addition to the [AR(1)] specification, a deterministic time trend variable should be considered in the equations system. According to Wooldridge (2008), the autoregressive correlation could be overestimated if the data demonstrates an upward or downward deterministic trend. Even though, Moosa and Baxter (2002) argue that a stochastic trend and stochastic seasonality should be considered for a long period of analysis. This study assumes a deterministic trend version because the data comprised only 19 years. Also, the time trend variable does not seem to have drastic slope changes through time.

8 Results and Discussion: Parameters and Fit Statistics

Full information maximum likelihood estimates of the parameters of the LR-D-IAIDS models are presented in table 2. The seasonal, trend, and autoregressive parameters are not

included because of space. The LR-D-IAIDS model are compared to the static[12] version by using the fit statistics presented in table 1. According to the Log-likelihood ratio test, the LR-D-IAIDS versions are an improvement over the static version[13]. The model with own- and cross- habit formation outperformed H&G model, which indicates that the own- and cross- consumption habits of bell pepper explain better the variation on market share than only considering the aggregated consumption habits. The LR-D-IAIDS with unrestricted own- and cross-habit formation outperformed the version augmented with restricted habits. The Durbin Watson (DW) values are greater for the model with LR-D-IAIDS with unrestricted own- and cross-habits, which implies that the specific consumption habit coefficients may be picking up some of the serial correlation effects present in the static model. Results also indicate that there is some persistence in the consumption patterns for fresh bell pepper in the United States. Thus, past allocation affects current consumption (see memory coefficient in table 2).

Table 1. Fits statistic Results: D-IAIDS H&G models vs the Static version

	Static IAIDS	LR H&G	LR Restricted Own-cross Habits	LR Unrestricted Own-cross Habits
No. of parameters	35	45	61	61
Log-likelihood	1063	1139	1,199	1,232
Log-likelihood ratio test		152	187.5	67.5
System adj. R^2	94.5%	95.8%	97.0%	97.0%
Eq. Mex adj. R^2	98.1%	98.7%	98.8%	98.9%
Eq. Usa adj. R^2	98.0%	98.2%	98.2%	98.3%
Eq. Mex DW	1.14	1.17	1.30	1.28
Eq. Usa DW	1.28	1.25	1.27	1.41

a) Durbin Watson statistics were generated before specifying the autoregressive parameters
b) Number of observations for the dynamic model are 236 per equation.
c) LR-D-IAIDS model with Restricted Own-cross-habits was estimated using 5 lags period for each habits.

[12] The static model contains a first-order autoregressive vector. Thus, it is dynamic in the sense that autocorrelation was specified. However, this dynamic specification is not behavioral, and the stakeholders might be concerned about behavioral dynamic or habit formation.
[13] As well, they are an improvement over the D-IAIDS model with linear and short memory habits. They were not presented because of space.

Table 2. Results of the LR-D-IAIDS models

Parameters (variables)		Static Model	*H&G Model*	IAIDS-Own-Cross-Habits *Restricted habits*	IAIDS-Own-Cross-Habits *Unrestricted habits*
α_{mex} (intercept)		0.634***	0.198	0.394***	0.283*
α_{usa} (intercept)		0.056	0.299*	0.096	0.355**
$\gamma_{mex-mex}$ (Lnq_{mext})		0.079***	0.235***	0.182***	0.254***
$\gamma_{mex-usa}$ (Lnq_{usat})		-0.067***	-0.127***	-0.065**	-0.134***
$\gamma_{mex-row}$ (Lnq_{rowt})		-0.011**	-0.107***	-0.117***	-0.119***
$\gamma_{usa-usa}$ (Lnq_{usat})		0.093***	0.163***	0.187***	0.166***
$\gamma_{usa-row}$ (Lnq_{rowt})		-0.025***	-0.036**	-0.121***	-0.031**
β_{mex} $(Ln\tilde{Q}_t^*)$	$\beta_{mex}(\mathrm{Ln}\ddot{Q}_t^*)$	0.040	-0.140**	0.000	-0.071
β_{usa} $(Ln\tilde{Q}_t^*)$	β_{usa} $(\mathrm{Ln}\ddot{Q}_t^*)$	-0.090***	0.125*	0.000	0.107
$\alpha_{mex}^{**}(\tilde{\mu}_{t-4})$	$\alpha_{imex}^{**}(\tilde{\mu}_{mex_{t-4}}^*)$			0.027	-0.067
	α_{iusa}^{**} $(\tilde{\mu}_{usa_{t-4}}^*)$		-0.020**	-0.001***	0.000***
	α_{irow}^{**} $(\tilde{\mu}_{row_{t-4}}^*)$			-0.011**	-0.016
$\alpha_{usa}^{**}(\tilde{\mu}_{t-4})$	$\alpha_{imex}^{**}(\tilde{\mu}_{mex_{t-4}}^*)$			0.033	0.043*
	α_{iusa}^{**} $(\tilde{\mu}_{usa_{t-4}}^*)$		0.005	-0.053	-0.000
	α_{irow}^{**} $(\tilde{\mu}_{row_{t-4}}^*)$			-0.033**	0.008
$\theta_{11}(Lnq_{mex}\tilde{\mu}_{t-4})$	θ_{111} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{mex_{t-4}}^*)$			0.044	0.029***
	θ_{112} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{usa_{t-4}}^*)$		0.008***	-0.022***	0.000***
	θ_{113} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{row_{t-4}}^*)$			0.005	0.006
$\theta_{12}(Lnq_{usa}\tilde{\mu}_{t-4})$	θ_{121} $(\mathrm{Ln}q_{usa} * \tilde{\mu}_{mex_{t-4}}^*)$			-0.023*	-0.015
	θ_{122} $(\mathrm{Ln}q_{usa} * \tilde{\mu}_{usa_{t-4}}^*)$		-0.003**	0.009***	-0.000***
	θ_{123} $(\mathrm{Ln}q_{usa} * \tilde{\mu}_{row_{t-4}}^*)$			0.007*	-0.001
$\theta_{13}(Lnq_{row}\tilde{\mu}_{t-4})$	θ_{131} $(\mathrm{Ln}q_{row} * \tilde{\mu}_{mex_{t-4}}^*)$				-0.013***
	θ_{132} $(\mathrm{Ln}q_{row} * \tilde{\mu}_{usa_{t-4}}^*)$		-0.005***		-0.000***
	θ_{133} $(\mathrm{Ln}q_{row} * \tilde{\mu}_{row_{t-4}}^*)$				-0.004
η_{mex} $(Ln\tilde{Q}_t^*)$	$\eta_{11}(\mathrm{Ln}\ddot{Q}_t^* * \tilde{\mu}_{mex_{t-4}}^*)$			0.000	-0.034
	η_{12} $(\mathrm{Ln}\ddot{Q}_t^* * \tilde{\mu}_{usa_{t-4}}^*)$		-0.008**	-0.000***	0.000**
	η_{13} $(\mathrm{Ln}\ddot{Q}_t^* * \tilde{\mu}_{row_{t-4}}^*)$			0.000*	-0.006
$\theta_{21}(Lnq_{mex}\tilde{\mu}_{t-4})$	θ_{211} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{mex_{t-4}}^*)$			-0.023***	-0.015***
	θ_{212} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{usa_{t-4}}^*)$		-0.003**	0.009	-0.000
	θ_{213} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{row_{t-4}}^*)$			0.007*	-0.001
$\theta_{22}(Lnq_{usa}\tilde{\mu}_{t-4})$	θ_{221} $(\mathrm{Ln}q_{usa} * \tilde{\mu}_{mex_{t-4}}^*)$			-0.004	-0.000
	θ_{222} $(\mathrm{Ln}q_{usa} * \tilde{\mu}_{usa_{t-4}}^*)$		0.003*	0.007	-0.000
	θ_{223} $(\mathrm{Ln}q_{mex} * \tilde{\mu}_{row_{t-4}}^*)$			0.010**	0.007**
$\theta_{23}(Lnq_{row}\tilde{\mu}_{t-4})$	θ_{231} $(\mathrm{Ln}q_{row} * \tilde{\mu}_{mex_{t-4}}^*)$			0.028***	0.016***
	θ_{232} $(\mathrm{Ln}q_{row} * \tilde{\mu}_{usa_{t-4}}^*)$		-0.000	-0.017***	0.000
	θ_{233} $(\mathrm{Ln}q_{row} * \tilde{\mu}_{row_{t-4}}^*)$			-0.018***	-0.005**
η_{usa} $(Ln\tilde{Q}_t^*)$	$\eta_{21}(\mathrm{Ln}\ddot{Q}_t^* * \tilde{\mu}_{mex_{t-4}}^*)$			-0.000	0.012
	η_{22} $(\mathrm{Ln}\ddot{Q}_t^* * \tilde{\mu}_{usa_{t-4}}^*)$		0.008**	0.000	-0.000
	η_{23} $(\mathrm{Ln}\ddot{Q}_t^* * \tilde{\mu}_{row_{t-4}}^*)$			0.000	0.015**
δ_{mex} (memory coefficient for $\tilde{\mu}_{mex_{t-4}}^*$)			0.007	-0.691***	-0.337**
δ_{usa} (memory coefficient for $\tilde{\mu}_{usa_{t-4}}^*$)			-0.813***	-0.471*	-10.86
δ_{row} (memory coefficient for $\tilde{\mu}_{row_{t-4}}^*$)			0.765***	0.227	0.651***

Numbers in the parameters are (1=Mex; 2=USA; 3=ROW). A timespan (m) of four months period was selected.

9 Results and Discussion: Price Flexibilities of the D-IAIDS Models

Uncompensated price and scale flexibilities for the D-IAIDS model are in table 3. They satisfy the aggregation relations of $\sum_i f_{ij} = f_i$ (homogeneity), $\sum_i \overline{w}_i f_{ij} = \overline{w}_j$ (Cournot), $\sum_i \overline{w}_i f_{ij} = -1$ (Engel) as proposed by Anderson (1980). This indicates that the estimated price flexibilities are consistent with the theory of ordinary demand curves.

The LR-D-IAIDS models yielded generally more inflexible (elastic) demand for bell pepper and larger substitution possibilities across sources than the static version[14] when holding all variables at the mean. The D-IAIDS model with unrestricted habits generated even more inflexible demand and larger substitution possibility than H&G model.

Table 3. Uncompensated long-run price flexibilities

	Mex-quantity		U.S.-quantity		ROW-quantity	
	IAIDS Static	LR-H&G Agg-Habit	IAIDS Static	LR-H&G Agg-Habit	IAIDS Static	LR-H&G Agg-Habit
Mex Price	-0.737***	-0.765***	-0.208***	-0.150***	0.119	-0.118
U.S. Price	-0.126***	-0.176***	-0.875***	-0.816***	-0.206**	-0.353***
ROW Price	-0.012	-0.034	-0.097***	-0.069***	-0.331***	-0.405**
Scale (fi)	-0.876***	-0.976***	-1.181***	-1.036***	-0.418**	-0.878***

LR-D-IAIDS Model with Own-cross-habit formation

	Mex-quantity		U.S.-quantity		ROW-quantity	
	Restricted Habits	Unrestricted Habits	Restricted Habits	Unrestricted Habits	Restricted Habits	Unrestricted Habits
Mex Price	-0.506*	-0.679***	-0.183**	-0.168***	-1.091	-0.401**
U.S. Price	-0.252*	-0.232***	-0.743**	-0.762***	-0.464	-0.431*
ROW Price	-0.228	-0.088**	-0.062	-0.068*	0.426	-0.166
Scale (fi)	-0.987***	-1.000***	-0.988***	-0.999***	-1.129***	-0.999***

a) The flexibilities were calculated using the "mean share" (53.1%, 38.4%, and 8.5% for U.S, Mexico, and ROW respectively) and the aggregated quantity index and habit term mean calculated with the parameters estimated for the respective models.
b) *, **, and *** denotes significance at 10%, 5%, and 1%, respectively.
c) Standard errors are excluded due to space

[14] Additionally, the price flexibilities for each model were generated at each single period. Then, a simple statistic comparison was performed. Between the proposed model and the statics version, the conclusion at the mean holds for the entire period (1998-2017) for all except for the following price flexibilities ($F_{mex\text{-}usa}$, $F_{usa\text{-}usa}$, $F_{row\text{-}row}$). Between the proposed model and H&G model, the conclusion for the entire period (1998-2017), except for ($F_{mex\text{-}usa}$, $F_{row\text{-}row}$).

Results from the inverse AIDS model with unrestricted own- and cross-habit formation indicate that the U.S. consumers substitute more easily the locally produced bell pepper with imported bell pepper than the other way around. The locally produced bell pepper is nearly two times more substitutable by imports from the ROW than by the imports from Mexico. This is intuitive since the bell pepper imported from Europe and Canada competes with the U.S. bell pepper during the summer window while Mexico supply is mostly during winter-spring.

The bell pepper imported from ROW has low substitution possibilities across sources while the Mexican bell pepper is nearly 2.5 more substitutable by import from other countries than by the local one. Countries in the DR-CAFTA agreement compete with Mexico during the winter-spring production window.

To the best of our knowledge, there are no studies devoted to calculating the bell pepper price flexibilities differentiating by sources, nor with habit formation. The closest is Nzaku, Houston, and Fonsah (2011), who estimated own-price elasticities for locally sourced bell pepper (-0.032, not significant) and imported bell pepper (-.63) with an ECM-AIDS. Naanwaab and Yeboah (2012), and You et al. (1998) estimated own-price elasticities for bell pepper and other vegetables using yearly data (-0.16 and -0.253, respectively). Although flexibilities and elasticities are not empirically the exact inverse, an inelastic demand could be interpreted as a flexible demand. Thus, the results of this study differ from previous studies because the estimated own-price flexibilities are all inflexible/elastic ($f_{ij} < |-1|$). Part of the discrepancy could be due to different estimation periods (they used data in the range of 1960-2010), data sampling frequency (they used yearly data, while this study used monthly data), and model specifications (they used the direct AIDS).

Table 4. Trend of the long run price flexibilities [Proposed LR-D-IAIDS model]

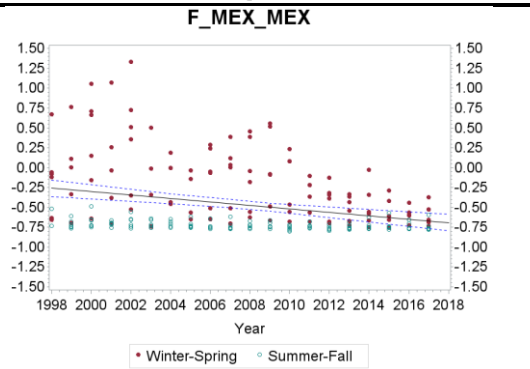
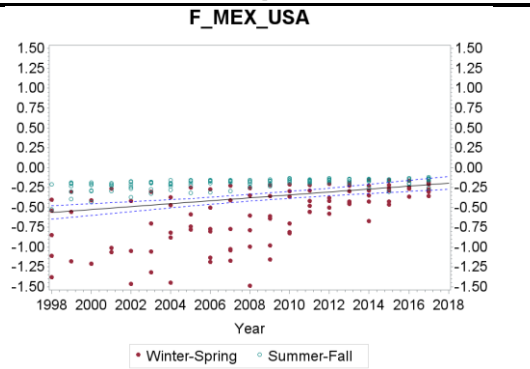
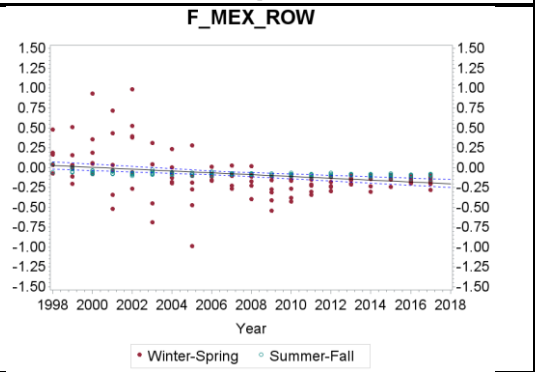
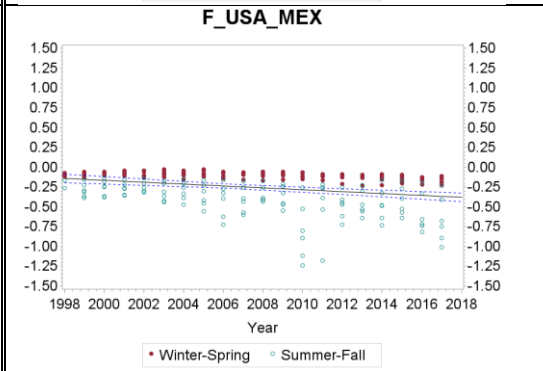
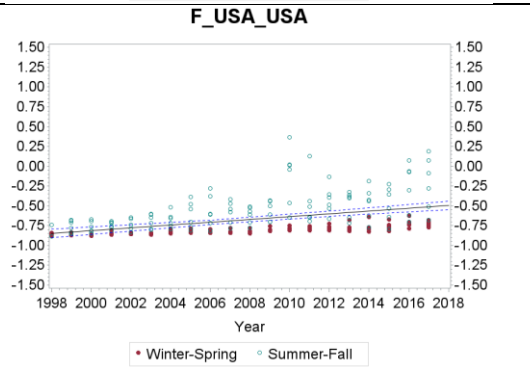
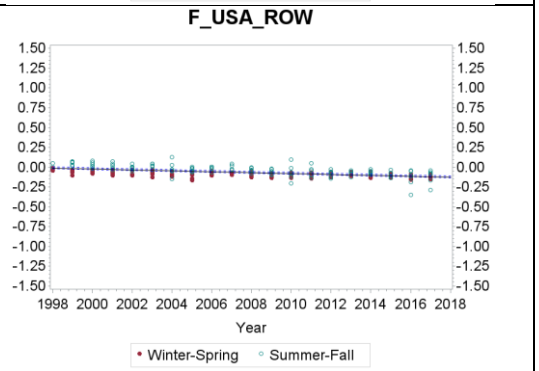
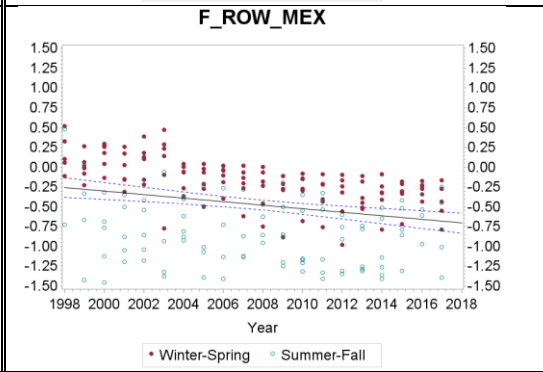
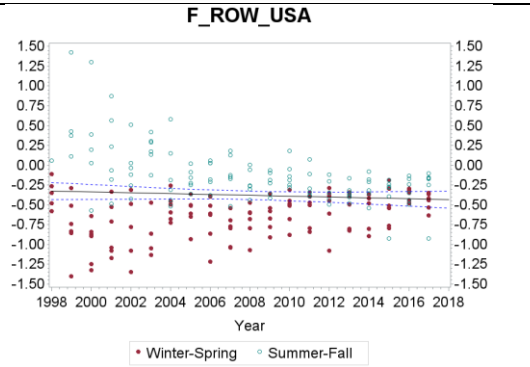
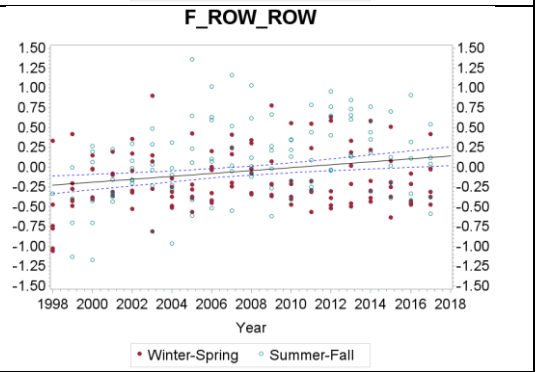
	1%ΔQ-Mexico	1%ΔQ-USA	1%ΔQ-ROW
%ΔP-Mex			
%ΔP-USA			
%ΔP-ROW			

Table 4 shows the evolution of the uncompensated long-run price flexibilities. During 1998-2017, the own-price flexibility for the imported bell pepper from Mexico has increased (in absolute value), while for bell pepper sourced locally it has decreased.

The evolution of the cross-price flexibilities between the source of Mexico and the US indicates that over time the imported bell pepper from Mexico has become less substitutable by the local one. The evolution of the cross flexibility $F_{usa\text{-}mex}$ indicates that the locally produced bell pepper has become more substitutable over time by imports from Mexico.

Notice that seasonality plays a vital role on the magnitude of the long-run own-price flexibilities, which can be explained by the graph in appendix 2. For example, for the U.S. bell pepper, the own-price flexibilities seems smaller (in absolute value) during summer-fall, while for the Mexican bell pepper it appears to be greater. That concurs with the time that bell pepper production is in-season (United States) or off-season (Mexico). Similarly, the long-run cross-price flexibilities are affected by seasonality. The local bell pepper seams more substitutable during summer and fall than the rest of the year. This implies that the proposed LR-D-IAIDS with own- and cross-habit formation could be improved by augmenting the preference specification with seasonal behaviors. This will remain as a goal for future research.

10 Results and Discussion: Habit Flexibilities of the D-IAIDS Models

The long run habit flexibilities are found in table 5 and 6. Results from the H&G and the proposed model indicates that habit formation plays an important role in the magnitude of the price flexibilities.

Table 5. LR aggregated habits flexibilities [LR-D-IAIDS H&G model]

	1%Δ↑_Q_{MEX}		1%Δ↑_Q_{USA}		1%Δ↑_Q_{ROW}	
		Agg-habit effects		Agg-habit effects		Agg-habit effects
	f_{ij}^{LR}	$\Delta f_{ij}/\Delta U_{t-M}$	f_{ij}^{LR}	$\Delta f_{ij}/\Delta U_{t-M}$	f_{ij}^{LR}	$\Delta f_{ij}/\Delta U_{t-M}$
%Δ Mex Price	**-0.759*** **	0.013***	-0.141***	-0.019***	-0.194	-0.016***
%Δ U.S. Price	-0.194***	0.000	**-0.789*** **	0.013**	-0.489***	0.000
%Δ ROW Price	-0.038	-0.064***	-0.071***	0.001	**-0.340** **	0.068***

Table 6. LR unrestricted own- and cross-habit flexibilities [Proposed LR-D-IAIDS model]

	1%Δ↑Q_{MEX}	Habit effects			1%Δ↑Q_{USA}	Habit effects			1%Δ↑Q_{ROW}	Habit effects		
		Agg-habit	Spec-habit			Agg-habit	Spec-habit			Agg-habit	Spec-habit	
	$f_{ij}'^{LR}$	$\partial f_{ij}/\partial\tilde{\mu}_{t-M}$	$\partial f_{ij}/\partial\tilde{\mu}_{jt-M}$		$f_{ij}'^{LR}$	$\partial f_{ij}/\partial\tilde{\mu}_{t-M}$	$\partial f_{ij}/\partial\tilde{\mu}_{jt-M}$		$f_{ij}'^{LR}$	$\partial f_{ij}/\partial\tilde{\mu}_{t-M}$	$\partial f_{ij}/\partial\tilde{\mu}_{jt-M}$	
			h_{111}=	**0.114*** **			h_{211}	-0.044***			h_{311}	-0.240***
%ΔP-Mex	**-0.679*** **	**0.069** **	**h_{112}=**	**-0.059** **	-0.168***	-0.017	h_{212}	0.018	-0.401**	-0.052**	h_{312}	0.154*
			h_{113}=	**0.013**			h_{213}	0.014*			h_{313}	-0.151***
			h_{121}=	-0.061***			**h_{221}**	**-0.009**			h_{321}	0.339***
%ΔP-US	-0.232***	-0.012	h_{122}=	0.024	**-0.762*** **	**0.025**	**h_{222}**	**0.014**	-0.431*	-0.013	h_{322}	-0.205***
			h_{123}=	0.019*			**h_{223}**	**0.020** **			h_{323}	-0.216***
			h_{131}	-0.060***			h_{231}	0.059***			**h_{331}**	**-0.097**
%ΔP-ROW	-0.088**	-0.237**	h_{132}	0.039**	-0.068*	-0.082	h_{232}	-0.036**	**-0.166**	**0.318** **	**h_{332}**	**0.050**
			h_{133}	-0.030***			h_{233}	-0.036***			**h_{333}**	**0.365*** **

Results indicate that increases in the bell pepper consumption habits, at the aggregated level, make the demand for bell pepper (own-price flexibilities) more inflexible/elastic. Thus the response of own-prices to changes in quantity becomes less with increases in aggregated consumption habits. The model of H&G shows that one percent increase in the aggregated habit decreases the own-price flexibilities by 1.7%, 1.6%, and 20%, respectively, for the Mexican, U.S., and ROW bell pepper.

The LR-D-IAIDS model with unrestricted own- and cross-habit formation show that the own-price flexibilities are more significant for imported bell pepper than for the local one. Thus changes in aggregated consumption habits do not affect the local bell pepper own-price flexibility. However, for Mexican bell pepper, one percent increase in the aggregated consumption habits decreases its own-price flexibility by nearly 10%. For the bell pepper imported from other countries, 10% percent increase in the aggregated consumption habits increases its own-price by nearly 3.2%.

Results in table 5 and 6 also indicate that increases in the aggregated consumption habits increase the level of substitution possibilities among sources. The model of H&G shows that one percent increase in the aggregated habit increases the cross-price flexibilities of $F_{row\text{-}mex}$, $F_{mex\text{-}usa}$ and $F_{mex\text{-}row}$ by 168%, 13% and 8%, respectively. The proposed model shows that, at the aggregate level, only the import sources substitution possibilities are affected. Thus, the cross-price flexibilities of $F_{mex\text{-}row}$ and $F_{row\text{-}mex}$ increase by 264% and 12%, respectively.

As hypothesized, results in table 6 indicate that the own- and cross-consumption habits affect the price flexibilities in different magnitude and direction, which contrasts with the H&G model. Some of the aggregated habit effect in table 6 are statistically zero because specific habits effect canceled each other. For example, the effect of changes in the aggregated habit on the cross-price

flexibility of "$F_{usa\text{-}mex}$" was zero for both models. However, when the analysis is done at the specific habit level, the substitution of U.S. bell pepper by Mexican imports increases with changes in the habit of consuming bell pepper imported from Mexico and decreases with changes in the habit of consuming bell pepper imported from the ROW. Similarly, the substitution of the local bell pepper with imports from Mexico increases/decreases (26%/8%) which changes in the consumption habit for Mexican/ROW bell pepper.

Also, notice that the cross-price flexibilities are affected more by changes in the habits of buying the Mexican bell pepper than changes in the habits of buying bell pepper from other sources. For the own-price flexibilities, the greatest habit effects come from changes in own consumption habits.

11 Conclusions

A novel approach is developed to evaluate the effect of consumption habits on the price flexibilities. Thus, the traditional Inverse AIDS model is augmented with own- and cross-consumption habits following Holt and Goodwin (1997) and Ray (1983). Even though the H&G LR-D-IAIDS model is a proven, general, and flexible specification to incorporate habit formation in the inverse demand system, it can be even more flexible if the stock of own- and cross-consumption habits are allowed to condition the budget share equation and the price flexibilities.

The H&G D-IAIDS model and the proposed specification outperformed the static IAIDS version. Likewise, the model with own- and cross-habit formation outperformed H&G's model. It might indicate that for bell pepper, and maybe for fruits and vegetables in general, accounting for the effect of specific-good consumption habits could be a better approach than only considering the aggregated stock of habit effects. Furthermore, the own- and cross-habit

formation coefficients may be picking up some of the serial correlation effects present in the static and H&G specification.

Results of the dynamic models suggest that habit formation plays a vital role in the magnitude of the own- and cross-price flexibilities. The D-IAIDS models with unrestricted own- and cross-habits generated, generally, smaller (bigger) own (cross) price flexibilities than the static and H&G version.

Results indicate that the locally produced bell pepper is substituted easier by imports than the other way around. The local bell pepper is nearly two times more substitutable by imports from the ROW than by imports from Mexico. The bell pepper imported from ROW has low substitution possibilities across sources while the Mexican bell pepper is nearly 2.5 more substitutable by imports from other countries than by the local one.

The evolution of the cross-price flexibilities between the source of Mexico and the US indicates that over time the imported bell pepper from Mexico has become less substitutable by the local one, while the U.S. bell pepper has become more substitutable by imports from Mexico.

It seems that seasonality plays a vital role on the magnitude of the long-run price flexibilities. The U.S. bell pepper own-price flexibility seems smaller (in absolute value) during summer-fall, while for the Mexican bell pepper it appears to be greater. The local bell pepper seams more substitutable during summer and fall than the rest of the year.

Results indicate that increases in the consumption habits of bell pepper, at the aggregated level, make the demand for bell pepper (own-price flexibilities) more inflexible/elastic. Results also indicate that increases in consumption habits, at the aggregate level, increase the level of substitution possibilities among sources.

As hypothesized, changes on the own- and cross consumption habits affect the price flexibilities in different magnitude and direction, which means that some of the aggregated habit effects are zero because the specific habit effects canceled each other. The cross-price flexibilities are affected more by changes in the habits of buying the Mexican bell pepper than changes in the habits of buying bell pepper from other sources. For the own-price flexibilities, the greatest habit effects come from changes in own consumption habits.

References

Alessie, R., & Kapteyn, A. (1991). Habit formation, interdependent preferences and demographic effects in the almost ideal demand system. *Economic Journal, 101*, 404-419.

Anderson, G., & Blundell, R. (1982). Estimation and hypothesis testing in dynamic singular equation systems. *Econometrica*, 50, 1559–1571.

Anderson, R. W. (1980). Some Theory of inverse demand for applied demand analysis. *European Economic Review*, 281-290.

Barter, A. P., & Bettendorf, L. J. (1989). Price formation of fish: An application of an inverse system. *European Economic Review, 33(1)*, 1509-1525.

Berndt, E., & Savin, N. (1975). Estimation and Hypothesis Testing in Singular Equation Systems with Autoregressive Disturbances. *Econometrica*, 43(3):519-30.

Blanciforti, L., & Green, R. (1983). An Almost Ideal Demand System Incorporating Habits: An Analysis of Expenditures on Food and Aggregate Commodity Groups . *The Review of Economics and Statistics*, 511-515.

Clements, K. W., & Si, J. (2015). Price Elasticity of food demand: Compensated vs Uncompensated. *John Wiley & Sons, Ltd.*, 1403-1408.

Deaton, A. (1979). The Distance Function in Consumer Behaviour with Applications to Index Numbers and Optimal Taxation. *The Review of Economic Studies*, 46(3), 391-405. Retrieved from http://www.jstor.org/stable/2297009

Deaton, A., & Muellbauer. (1980b). *Economics and Consumer Behavior.* New York, NY: Cambridge University Press.

Deaton, A., & Muellbauer, J. (1980). An Almost Ideal Demand System. *The American Economic Review*, 70(3), 312-326.

Dedah, C., Keithly, W., & Kazmierczak, R. (2011). An Analysis of US Oyster Demand and the Influence of Labeling Requirements. *Marine Resource Economics, 26(1)*, 17-33.

Eales, J. S., & Unnevehr, L. J. (1991). The inverse almost ideal demand system. *Proceedings of the NCR-134 Conference on Applied Commodity Price Analysis, Forecasting, and Market Risk Management. Chicago, IL. , 38(1)*, 402-417.

Eales, J. S., & Unnevehr, L. J. (1993). Simultaneity and structural change in US meat demand." American Journal of Agricultural Economics 75,. *75 No. 2*, 259-268.

Enders, C. K. (2010). *Apply Missing Data Analysis* . New York: The Guilford Press.

Estes, E. A. (2003). Tomato wars: A discussion of how international trade, structural changes, and competitiveness affect the North American produce industry. *Journal of Agricultural and Applied Economics, 35(02)*, 313-319.

Godfrey, L. G. (1978). A Heteroskedasticity-Consistent Covariance Matrix Estimator and a Direct Test for Heteroskedasticity. *Econometrica, 46(6)*, 1293–301.

Grant, J. H., Lambert, D. M., & Foster, K. A. (2010). A seasonal inverse almost ideal demand system for North American fresh tomatoes. *Canadian Journal of Agricultural Economics/Revue canadienne d'agroeconomie, 58(2)*, 215-234.

Green, R., Hassan, Z., & Johnson, S. (1978). Maximum Likelihood estimation of linear expenditure systems with serially correlated errors. *European Economic Review* , 207-219.

Greene, W. (2012). *Econometric analysis.* New York: Pearson eduacation, Inc. .

Gruda, N. (2005). Impact of environmental factors on product quality of greenhouse vegetables for fresh consumption. *Critical Reviews in Plant Sciences, 24:3*, 227-247.

Gunter, L. F., & Ames, G. C. (1997). The US Mexican Winter Market Trade Dispute (No. 16682). *University of Georgia, Department of Agricultural and Applied Economics.*, 21.

Hicks, J. (1957). A Revision of Demand Theory. *Journal of Political Economy, 65:2*, 169-170.

Holt, M. T. (1998). Autocorrelation specification in singular equation systems: A further look. *Economics letters*, 135–141.

Holt, M. T., & Goodwin, B. K. (1997). Generalized Habit Formation in an Inverse Almost Ideal Demand System: An Application to Meat Expenditures in the U.S. *Empirical Economics*, 22: 293-320.

Houck, J. P. (1966). A look at flexibilities and elasticities. *Journal of Farm Economics, 48(2)*, 225-232.

Huang, K. S. (1988). An inverse demand system for US composite foods. *American Journal of Agricultural Economics, 70(4)*, 902-909.

Jovicich, E., Cantliffe, D. J., Sargent, S. A., & Osborne, L. S. (2004, July). *Production of Greenhouse-Grown Peppers in Florida. Document HS979*. Retrieved from http.//edis.ifas.ufl.edu

Jovicich, E., Cantliffe, D., & VanSickle, J. (2004). U.S. imports of colored bell peppers and the opportunity for greenhouse production of peppers in Florida. . *Acta Hortic.* , 659, 81-85. .

Karagiannis, G., & Velentzas, K. (1997). Explaining food consumption patterns in Greece. *J. Agric. Econ.* , 48, 83-92.

Karagiannisa, G., Katranidisb, S., & Velentzasb, K. (2000). An error correction almost ideal demand system for meat in Greece. *Agricultural Economics*, 29–35.

Kesavan, T., & Buhr, B. (1995). Price determination and dynamic adjustments: An inverse demand system approach to meat products in the United States. *Empirical Economics*, 20(4), 681-698. doi:10.1007/BF01206064

Malkin, E. (2017, Feb 1). *Mexico Takes First Step Before Talks With U.S. on Nafta*. Retrieved from The New York Time: https://www.nytimes.com/2017/02/01/world/americas/mexico-nafta-renegotiation-trump-wall.html?_r=0

Manser, M. (1976). Elasticities of Demand for Food: An Analysis Using Non-Additive Utility Functions Allowing for Habit Formation. *Southern Economic Journal*, 43(1), 879-891. doi:10.2307/1056349

McLaren, K. (1996). Parsimonious autocorrelation corrections for singular demand systems. *Economics Letters*, 53, 115-121.

Moosa, I. A., & Baxter, J. L. (2002). Modelling the trend and seasonals within an AIDS model of the demand for alcoholic beverages in the United Kingdom. *J. Appl. Econ.*, 17: 95–106. doi:10.1002/jae.634

Moschini, G., & Vissa, A. (. (1992). A Linear Inverse Demand System. *Journal of Agricultural and Resource Economics*, 17(2), 294-302.

Naanwaab, C., & Yeboah, O. (2012). Demand for Fresh Vegetables in the United States: 1970–2010. *Economics Research International*.

Newey, W. K., & West, K. D. (1987). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica, 55 (1)*, 703–708.

Newman, D. A. (2003). Longitudinal Modeling with Randomly and Systematically Missing Data: A Simulation of Ad Hoc, Maximum Likelihood, and Multiple Imputation Techniques. *Organizational Research Methods*, 328-362.

Nzaku, K., Houston, J., & Fonsah, E. (2011). US demand for fresh fruit and vegetable imports. *Journal of Food Distribution Research*.

Park, H., & Thurman, W. N. (1999). Interpreting inverse demand systems: a primal comparison of scale flexibilities and income elasticities. *American Journal of Agricultural Economics, 81(4)*, 950-958.

Pollak, R., & Wales, T. (1969). Estimation of the Linear Expenditure System . *Econometrica*, 611-628.

Ray, R. (1983). A dynamic generalisation of the almost ideal demand system. *Economics Letters*, 235-239.

VanSickle, J. J., Belibasis, E., Cantliffe, D., Thompson, G., & Oebker, N. (1994). *Competition in the US winter fresh vegetable industry: 1985-1992.* Washington, DC.: Agricultural Economic Report No. 691. ERS, US Department of Agriculture.

Wold, H. (1954). *A study in the analysis of stationary time series, 2nd ed.* Uppsala: Almquist and Wicksell.

Yang, S. R., & Koo, W. W. (1994). Japanese meat import demand estimation with the source differentiated AIDS model. *Journal of Agricultural and Resource Economics*, 396-408.

You, Z., Epperson, J. E., & Huang, C. L. (1998). Consumer demand for fresh fruits and vegetables in the United States (1960-1993). *UGA Cooperative Extension RB 431*.

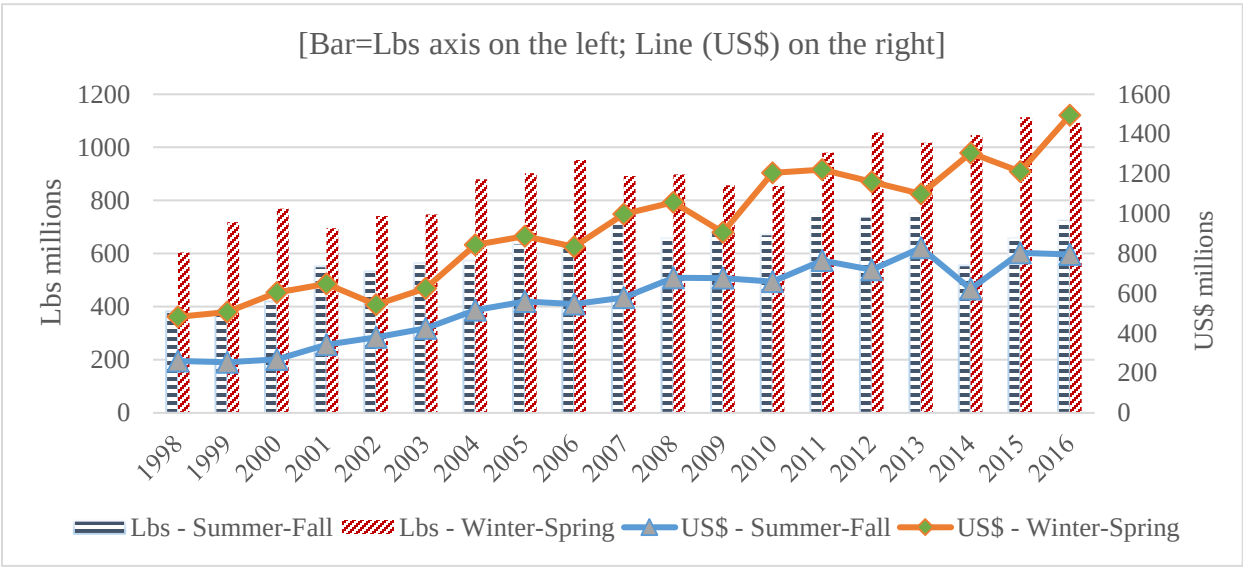
Zellner, A. (1962). An Efficient Method of Estimating Seemingly Unrelated Regressions and Tests for Aggregation Bias. *Journal of the American Statistical Association, 57*, 348–368.

Appendix 1. Test for unit root, monthly data, 1998-2017

Variables	W_{mex}	W_{usa}	W_{row}	LnQ_{Mex}	LnQ_{USA}	LnQ_{Row}	LAQI
Tau	-11.92	-10.08	-7.03	-10.51	-9.13	-7.98	-8.56
Pr<Tau	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001	<.0001

The ADF test[15] shows that none of the variables analyzed have a unit root, so all variables are trend stationary.

Appendix 2. Total consumption of bell pepper in the United States by source and season



[15] The unit root test is based on: $\Delta x_t = \alpha + \beta x_{t-1} + \gamma Time + \sum_{j=1}^{n} \theta_j \Delta x_{t-j} + v_t$, where x_t is the dependent variable from the LA/IAIDS. Table 2 present the γ_τ statistic and the probability of $\gamma_\tau < \gamma_C$.