International Food and Agribusiness Management Review
Volume 22 Issue 3, 2019; DOI: 10.22434/IFAMR2018.0120

Received: 21 November 2018/ Accepted: 26 January 2019

An alternative approach to measuring demand changes in meat markets

RESEARCH ARTICLE

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Abstract

Commodity groups, academics, government agencies, and marketing analysts often have strong interests in understanding changes in demand for products. It is often the case, however, that only equilibrium price and quantity data are available for identifying changes in demand. But, such equilibria are the result of both changes in demand and changes in supply – the latter of which causes changes in quantity demanded. Although an existing index-based method is widely used to identify demand shifts, we consider its theoretical foundation and empirical performance against a proposed alternative. We find that when using widely available but highly aggregated annual-level price and quantity data, our alternative better characterizes demand shifts for goods such as beef, pork, poultry, and lamb. For many agribusinesses that require information about market dynamics in their industry, our method is likely to provide a more accurate, low-cost assessment of demand changes over time.

Keywords: beef, demand index, lamb, meat, pork, poultry, quantity demanded
JEL code: Q11, Q41

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1. Introduction

Demand modeling research has an extensive presence in the agricultural economics literature, with dozens of advances published in hundreds of research articles over the past several decades. The majority of this research uses complete systems of demand equations to better understand structural changes and impose theoretical demand restrictions on estimation procedures to obtain more precise estimates of own-price, cross-price, and income elasticities. Researchers have also extended models to include demand shifters such as advertising expenditures (Brester and Schroeder, 1995), public health concerns (Tonsor *et al.*, 2010), food safety issues (Piggott and Marsh, 2004), animal welfare information (Allender and Richards, 2010), habit formation (Zheng *et al.*, 2016) and to address various endogeneity issues (LaFrance, 1991).

These advances have been critical for identifying and quantifying the effects of specific factors on demand and understanding the responsiveness of quantity demanded to shifts in supply. However, using demand system models to determine annual changes in demand is relatively complex and may not be practical for applications outside of academia. As a result, many industry and producer groups have relied on other measures to identify demand changes.[1] Thus, there appears to be a gap between tools that have been developed and rigorously tested by trained economists (but which are infrequently used in practice) and the demand by industry stakeholders for simpler, less-costly methods.

In an attempt to bridge this gap, an unpublished white paper presented a simple but intuitive index-based procedure that uses readily available observed annual price and quantity data to answer the general question, 'Regardless of the factors that may have shifted demand, by how much (if at all) did demand change?' (Purcell,1998). The index addresses a very specific question about whether or not demand has changed from period to period and the relative extent of this change. Industry groups and agricultural producers frequently ask for this specific information.

The procedure's apparent economic intuitiveness, practical ease of application, and high relevance regarding demand changes has led to its extensive use by industry groups and many university extension programs for nearly twenty years. For example, the meat demand index produced by Kansas State University (Ag Manager, 2017) provides quarterly demand estimates for beef and pork, which are accessed by a large number of industry participants. The National Cattlemen's Beef Association and the National Pork Producers Council also use such indices to evaluate their five-year strategic objectives to increase beef and pork demand (NCBA, 2016; Maulsby, 2015; Tonsor *et al.*, 2018). The American Sheep Industry's Demand Creation Committee in conjunction with the American Lamb Board has also used the index methodology to assess strategies for increasing lamb demand (ASIA, 2016).

Despite the growth of the demand index use in US agricultural commodity sectors, its methodology and empirical accuracy have never been formally evaluated. Our work demonstrates the economic intuition underlying Purcell's (1998) demand index approach and then empirically evaluates the method. This assessment is motivated by our observations of inconsistencies in demand change calculations generated by the originally-proposed method. For example, Figure 1 presents the demand indices (solid lines) for beef, pork, poultry, and lamb that were calculated using the method described in Purcell (1998), along with annual per capita consumption (dashed lines) for comparison. The price demand indices and per capita consumption patterns for beef, pork, and lamb do not indicate any obvious anomalies. However, applying the approach to the poultry market is problematic. Figure 1 shows that poultry consumption increased throughout the 1980s and 1990s probably as a result of changes both in demand and technological changes that increased supply. However, the figure shows that the price index generates nonsensical demand change predictions, ranging from 8,000% increases to 1000% decreases between 1980 and 2014. Given that the procedure results in

[1] For example, many industry groups, including the US Energy Information Administration, have assumed that changes in per capita consumption are synonymous with changes in demand (for example, see US Energy Information Administration, 2016). However, using consumption as a measure of demand conflates changes in demand with changes in quantity demanded, which can result either from shifts in demand or supply.

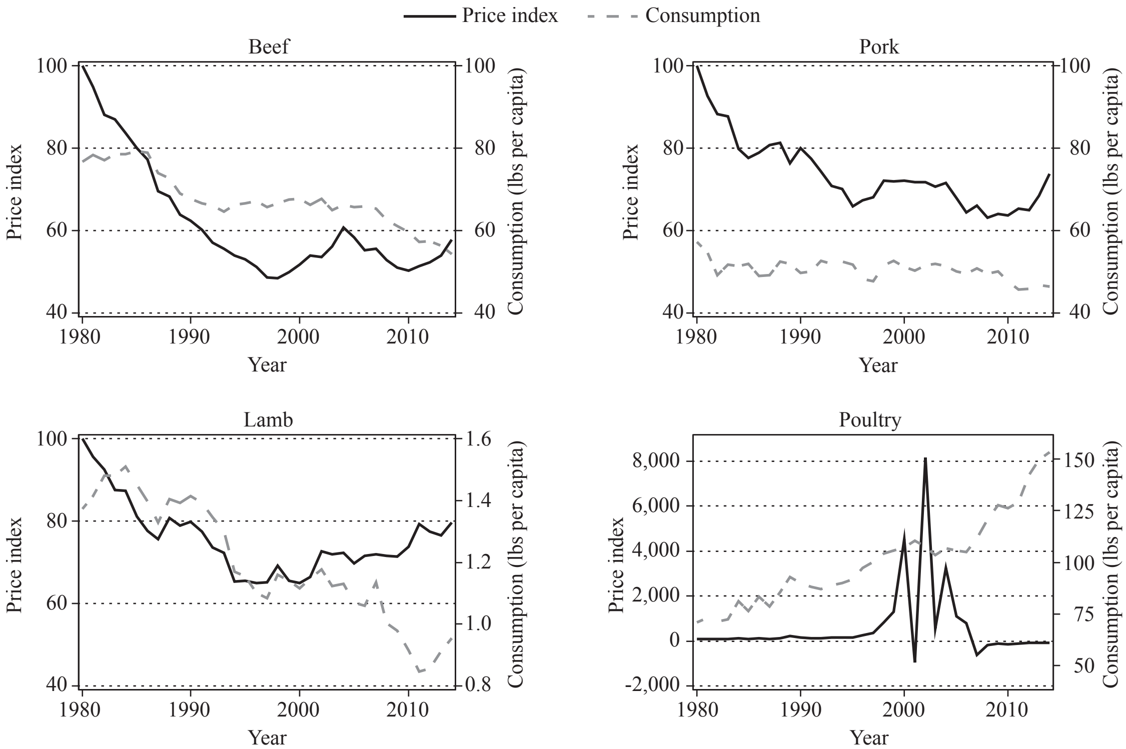

Figure 1. Meat demand indices using the price index calculation method and per capita consumption. In the 1980 base year, all index values are 100. The left-side vertical axis corresponds to the price index (solid line) and the right-side vertical axis corresponds to consumption in pounds per capita (dashed line). Index calculations are based on elasticity estimates derived from the literature and presented in Table 3.

illogical demand predictions for poultry, it is unclear whether the underlying technique also biases estimates (and if so, to what extent) for other meat species, even if no obvious anomalies are observed.

To better understand the potential reasons for the apparent empirical inconsistencies and determine whether a better alternative exists, we first show that there are two potential approaches for developing a demand index based on the intuition proposed in Purcell (1998). The first is the original methodology that measures demand shifts using changes in prices (which we entitle as the 'price index' approach). The procedure measures changes in demand by considering vertical shifts in demand functions. The second approach represents our alternative that measures changes in demand using horizontal demand shifts in the quantity space (entitled the 'quantity index' approach). We then use simulations to evaluate the accuracy of the two competing methods by generating known shifts in demand and associated equilibrium prices and quantities, and comparing these actual demand shift amounts to those predicted by the two index approaches. The purpose of the simulation is to answer a single question: in the presence of known, simulated shifts in supply, demand, or both, how well does each index procedure account for changes in quantity demanded (caused by supply shifts) and correctly measure changes in demand?

The results of our simulations show that predicted demand shifts from the quantity index (relative to the price index) are more accurate in markets with relatively inelastic demands (as is the case for most food products) and when rapid or large structural changes in supply or demand conditions occur (such as technological innovations). Several robustness techniques – such as simulating only supply shifts (which should result in estimates of zero demand changes), only demand shifts (which should be perfectly identified as demand shifts), and using both constant elasticity and linear slope assumptions – help evaluate the accuracy of each index. We find that our proposed quantity index consistently estimates changes in demand while the price index provides far less accurate predictions.

We then apply the quantity index approach to four US meat sectors that have frequently been evaluated using Purcell's (1998) methods: beef, pork, lamb, and poultry. The results indicate that beef, pork, and lamb demand has decreased by an estimated 20-30% relative to a 1980 benchmark, and the demand for poultry has increased by approximately 90%. These results are substantially different from those implied by the existing price index method.

As food industry leaders propose initiatives to assess and influence food consumption behaviors, accurately evaluating these efforts will become critical for valuing returns to those efforts and weighing relative costs. Inaccuracies in these assessments could contribute to costly and inefficient uses of investors' and stakeholders' resources. Our empirically-verified method for evaluating demand changes can provide agribusiness industry leaders with better information without any increases in costs.

2. Demand index calculations

Although the issue of delineating changes in demand from changes in quantity demanded is conceptually simple, the practicality of using data to *ex post* quantify differences between the two is highly challenging. The issue is further complicated by whether a researcher or practitioner is interested in identifying factors that cause demand and/or supply shifts (i.e. changes in quantity demanded). In the latter case, approaches such as systems of demand equations have been shown to be useful modeling techniques. For example, such models are often estimated using own-price (the factor that causes changes in quantity demanded) and exogenous demand shifters (e.g. income, prices of substitutes, etc.) as regressors, which can be useful for identifying the impact of changes in demand for certain factors such as advertising or information effects.

In many cases, however, industry and academic professionals seek to identify only the size (if any) of a demand change without considering the source of that change nor the change in the supply (quantity demanded). Relying on an evaluation of changes in per capita consumption is not helpful for this endeavor. In addition, systems of demand equations and other structural econometric models may not be particularly effective either. For example, if one knows the true functional form of the demand functions being estimated, then one could theoretically populate estimated regression equations with actual values that occurred during the sample period. This process could theoretically be used to determine the degree to which the dependent variable – such as per capita consumption – was altered by changes in own price versus other (demand shifting) factors. However, the functional forms of demand equations are not known with certainty (in fact, most systems of demand equations use relatively flexible functional forms for the purpose of developing elasticity estimates rather than marginal effects of included regressors). It would also require that all of the (potentially dozens or hundreds) of factors that influence demand be identified and data for these factors collected to quantify the totality of individual effects. Similar problems exist when estimating supply equations that could be used to delineate changes in quantity demanded from changes in demand.

In light of these complexities, Purcell (1998) outlines an intuitive and easily applied approach for estimating a single, highly-specific market outcome sought by many agribusiness managers and producer groups: a change in demand. Specifically, the index seeks to measure a single, specific aspect of market changes: the extent to which an observed movement from one market equilibrium to another is due to a demand shift. That is, the procedure attempts to separate changes in demand from changes in quantity demanded (i.e. movements along the demand curve) using only observed and easily accessible annual (or quarterly) price and quantity data.

An important reason to use these data is that they implicitly encompass all of the factors causing demand changes rather than only those that can be included in an econometric model. That is, the use of realized prices and quantities between two time periods necessarily includes all of the factors that cause demand to change along with the single factor (own-price changes caused by supply shifts) that causes quantity demanded to change. However, given that highly-aggregated market data are used, this approach is not intended to measure or address more sophisticated dynamics. For example, the index-based procedure cannot identify the underlying causes for a demand shift, for which systems of demand equations modeling may be more appropriate. Nor is the index developed to quantify changes in quantity demanded (i.e. shifts in the supply curve).

2.1 The price index approach

Purcell's (1998) original methodology considers vertical shifts in demand functions for identifying demand shocks from market price and quantity outcomes. Figure 2A presents the procedure's basic concept assuming a constant-slope linear demand function. Consider an equilibrium price (P_0) and quantity (Q_0) that occurs in the base period t_0; this equilibrium is represented by point A. P_0 represents an initial equilibrium price and Q_0 represents per capita consumption on the linear demand curve D_0.

Suppose that in a subsequent period, t, a new equilibrium price (P_t) and quantity (Q_t) occur at point B. The movement from point A to point B is caused by changes in both demand (D_0 to D_t) and supply (S_0 to S_t). That is, while per capita consumption is higher at point B relative to point A, demand is lower at point B. If one assumes that the slope of the new demand curve is the same as D_0, then D_t passes through B and represents the new (lower) demand curve. After considering the demand reduction, the higher level of per capita consumption that occurs at point B must be the result of changes in production, net trade, and/or storage.

Purcell (1998) proposes that an intuitive approach to separate the demand and quantity demanded changes can be done in two steps. First, determine the point on the original demand curve that would result in the new observed level of per capita consumption Q_t but under the assumption that there was no change in demand (i.e. only a change in quantity demanded). In Figure 2A, this occurs at point C on the original demand curve D_0. Without a change in demand, the expected price at point C would be P_t^e. After P_t^e is identified, the method assumes that all other factors contributing to the difference between P_t^e and the actual observed price P_t are associated with a demand shift (in Figure 2A, shown as a demand decrease from D_0 to D_t) that occurred between the two periods. Thus, this method assumes that a demand change can be measured as the vertical distance between relative prices while holding quantity fixed. This change can be represented either by a percentage measure or an index number.

An important consideration when estimating the demand shift is the form of demand curve D_0. When the functional form is uncertain, one of two assumptions must be used to calculate P_t^e. The usual assumption is that D_0 is linear and, thus, the slope of D_0 is constant. In this case, an estimate of the demand curve's price flexibility (typically determined by inverting the curve's estimated own-price elasticity of demand at point A) can be combined with the known values of P_0 and Q_0 to calculate the slope of D_0. This information is then combined with Q_t to calculate P_t^e.[2]

One could also assume that the elasticity of demand along the entire demand curve is constant. Figure 2B presents a constant elasticity representation of D_0. In this case, the known values of Q_0 and Q_t are used to calculate the observed percentage change in the quantity variable. This percentage change is then applied to the price flexibility to obtain a value for P_t^e. The change in demand is then calculated as noted above. Of course, other functional forms are certainly possible, but these two assumptions generally reflect those commonly used by practitioners.

Equation 1 presents the mathematical representation of Purcell's (1998) method:

$$I_{price} = \left(\frac{P_t}{P_t^e}\right) \times 100 = \left(\frac{P_t}{P_0 + \left\{P_0 \times \left[\left(\frac{Q_t - Q_0}{Q_0}\right) \times \left(\frac{\%\Delta P}{\%\Delta Q}\right)\right]\right\}}\right) \times 100 \qquad (1)$$

[2] We recognize that the own-price elasticity of demand for the linear demand curve D_0 is different at point C relative to point A. For small changes in demand and supply, however, the difference is assumed to be relatively small.

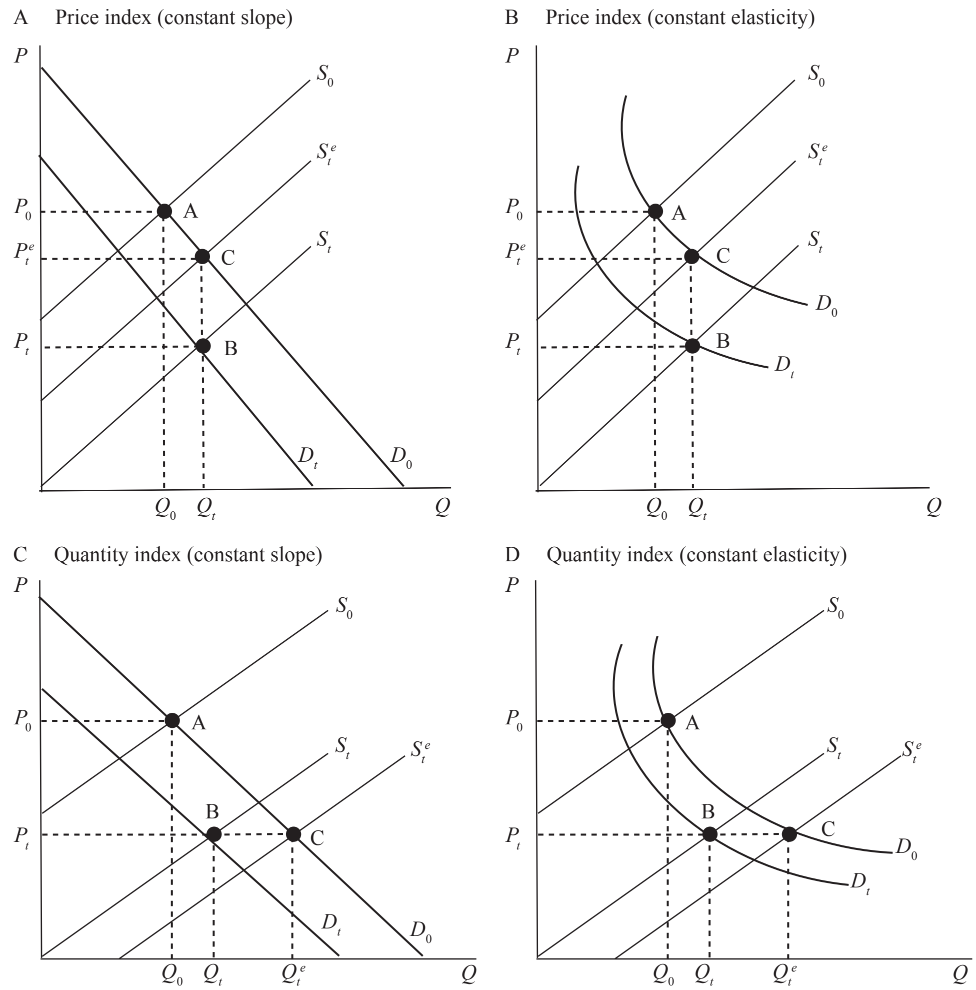

Figure 2. Graphical representation of difference between price index and quantity index approaches. (A) Price index (constant slope); (B) Price index (constant elasticity); (C) Quantity index (constant slope); (D) Quantity index (constant elasticity).

The expected price in t (P_t^e) is calculated by first multiplying the percentage change in consumption between the base period and period t by the own-price flexibility of demand ($\%\Delta P / \%\Delta Q$). The latter corresponds to the responsiveness of the price and quantity relationship as given by the price flexibility of D_0 depicted in Figure 2A and 2B. This result is multiplied by the base year price and then added to the base year price to obtain the expected price in year t; that is, the price that would have occurred if the demand curve had not changed. The demand index for the base year is (arbitrarily) set to 100.

2.2 A quantity index alternative

An alternative method to construct a demand index uses Purcell's intuition but applies it to the neoclassical approach to considering demand shifts. That is, the price index described above measures a change in demand based upon the vertical difference between P_t and P_t^e (Figures 2A and 2B). But, the neoclassical definition of a change in demand considers changes in consumption that occur while holding price constant. That is, changes in demand should be measured as horizontal shifts across the quantity space. Consequently, our quantity index is based on the changes in expected and observed quantities rather than in price.[3]

[3] We thank Myles Watts for this insight and for reminding us that everything we know about economics was learned in ECON 101.

Figure 2C illustrates this alternative characterization of demand changes assuming a linear demand function. Consider the initial price, P_0, and quantity, Q_0, equilibrium that occurs at point A. Suppose that in period *t*, a movement from point A to point B occurs. The appropriate measure of any potential change in demand should be indicated by a reduction in demand to D_t. Thus, the demand change should be measured horizontally from point B to point C at P_t. Note that if there had been no change in demand, then per capita consumption would be expected to be Q_t^e at P_t.

If demand had not changed, then the calculation of the expected quantity (Q_t^e) given price P_t follows from using an estimate of the own-price elasticity of demand at point A, which is used to obtain the slope of D_0 and observed values of P_t and Q_t. Consequently, the difference between Q_t^e and Q_t is a measure of the demand change that occurred between the two periods. Likewise, a similar methodology can be used if one assumes that the elasticity of demand along the entire demand function is constant (Figure 2D).

A quantity-based demand index can be constructed as:

$$I_{quantity} = \left(\frac{Q_t}{Q_t^e}\right) \times 100 = \left(\frac{Q_t}{Q_0 + \left\{Q_0 \times \left[\left(\frac{P_t - P_0}{P_0}\right) \times \left(\frac{\%\Delta Q}{\%\Delta P}\right)\right]\right\}}\right) \times 100 \tag{2}$$

The index is calculated by dividing the actual per capita consumption in year *t* (Q_t) by the expected per capita consumption that would have occurred in year t had demand remained unchanged. The expected (no demand change) quantity Q_t^e is calculated by first multiplying the percentage change in real prices between the base period and period t by the own-price elasticity of demand ($\%\Delta Q / \%\Delta P$). This results in a percentage change in quantity that is multiplied by the base year quantity. This value is then added to the base year quantity to obtain the expected quantity in year t that would have occurred if the demand curve had not changed between the base year and year *t*.

3. A simulation analysis of demand indices

In a world with perfect information, we would test the accuracy of demand change predictions of the two competing methods by observing both consumer and producer behavior in a particular market across time, perfectly identifying to what extent changes in the equilibrium prices and quantities occurred due to a supply or demand shift, and then comparing how well each of the two indices more accurately predicts the demand shift. Arguably, no industry or dataset exists that provides that level of detail, and this is especially the case for highly complex food sectors. However, by simulating known supply and demand shifts, and collecting the resulting equilibrium price and quantity data from these changes, we are able to empirically assess the competing indices. The simulation also provides an opportunity to evaluate prediction performance under alternative assumptions regarding demand elasticities and shapes of the demand curve.

Specifically, we simulate demand shocks independently from supply shocks and then precisely measure the ability of each index to predict the generated demand shocks. The simulation procedure follows these steps:

1. Specify values for the assumed intercept, α_0, slope, β_0, and own-price elasticity, η_0, of the initial linear demand curve in base period t_0.[4] These conditions are used to determine the initial equilibrium quantity, $Q_0 = \alpha_0/(1 - \eta_0)$, and price, $P_0 = (Q_0 - \alpha_0)/\beta_0$.
2. Randomly generate a pure demand shock (in proportion) in time *t*, which is reasonable in magnitude. For example, a shock $\delta_t \sim N(0, 0.05)$ would result in a demand change that is approximately bounded $\delta_t \in [-0.10, 0.10]$. Calculate $\widetilde{Q}_t = (1 + \delta_t)Q_{t-1}$. The distance between $\widetilde{Q}_t$ and Q_{t-1} represents the difference in consumption levels due to a demand change if the price were to remain at P_{t-1}.

[4] The linear demand curve assumption may (arguably) be overly restrictive (Lusk and Tonsor, 2016). However, linearization assumptions have been used extensively in the extant literature and are reasonable when intertemporal changes in equilibrium price and quantity conditions are moderate.

3. Determine the slope and intercept of the new demand curve. These values can be determined under two assumptions.
   a. If we assume that the demand curve slope is constant (but that the own-price elasticity of demand varies at each new quantity and price combination), then $\beta_t = \beta_0$. Then, using the fact that the new demand curve must necessarily go through the point $(\widetilde{Q}_t, P_{t\text{-}1})$, the slope is calculated as $\alpha_t = \widetilde{Q}_t - \beta_t P_{t\text{-}1}$.
   b. If we assume that the own-price elasticity remains the same (but that the slope changes) and use the fact that the new demand curve must necessarily go through the point $(\widetilde{Q}_t, P_{t\text{-}1})$, then $\beta_t = \eta_0 \times (\widetilde{Q}_t / P_{t\text{-}1})$. As in step 3a, the slope is calculated $\alpha_t = \widetilde{Q}_t - \beta_t P_{t\text{-}1}$.
4. Randomly generate price in time t, which is reasonable in magnitude. For example, a shock $\pi_t \sim N(0, 0.05)$ would result in a price change that is approximately bounded $\pi_t \in [-0.10, 0.10]$. Calculate $P_t = (1+\pi_t)P_{t\text{-}1}$, which represents the new equilibrium price.
5. Calculate the new equilibrium quantity value by determining where the new price, P_t, falls on the new demand curve (step 3). That is, $Q_t = \alpha_t + \beta_t P_t$.[5]
6. Determine the quantity on the new demand curve that occurs at the original equilibrium price; that is, $\widehat{Q_t} = \alpha_t + \beta_t P_0$. The change between $\widehat{Q_t}$ and the original equilibrium quantity, Q_0, represents the pure demand shift relative to the base period, t_0, because the slope and intercept values were determined using the pure demand shock (step 2). To represent this demand shock in the same units as the demand indices, calculate $I_{true,t} = 100 + [(\widehat{Q_t} - Q_0)/Q_0] \times 100$.
7. Calculate the price and quantity index values for period t, $I_{price,t}$ and $I_{quantity,t}$, using the generated market equilibrium values, Q_t and P_t.
8. Repeat steps 2–5 for t=1 ... T. For each of these iterations, use the quantity and price combination in each period to calculate the price and quantity indices. Then, for each period, calculate the squared errors, $e^2_{price,t} = (I_{price,t} - I_{true,t})^2$ and $e^2_{quantity,t} = (I_{quantity,t} - I_{true,t})^2$.
9. Repeat the simulation in steps 1–6 m-times to obtain a sampling distribution of the mean squared error associated with the price and quantity indices.

We simulate 500 iterations of time series data that represent demand shocks, supply shocks, and market equilibria. We then estimate the sampling distribution of mean squared errors for the price- and quantity-based indices. In each simulation, we calculate the indices and resulting squared errors under two different assumptions regarding the shape of the demand curve: (1) the slope of the demand curve remains constant across each time series while the own-price elasticity of demand is conditional on the price and quantity combination in period t, and (2) the own-price elasticity of demand remains constant across each time series while the slope is conditional on the price and quantity combinations in period t. Then, we perform each simulation process using a range of initial demand curve conditions and time series lengths. Specifically, we simulate data and calculate squared errors for demand curve slopes in the range, $\beta \in [-1.40, -0.20]$, own-price demand elasticity values in the range, $\eta \in [-1.40, -0.20]$, and times series lengths in the range, $T \in [5, 50]$ periods. These ranges were chosen based on a combination of empirical estimates reported in the extant literature and our assumptions about reasonable maximum and minimum values. In all cases, the initial intercept of the linear demand curve was assumed to be α_0=100.[6]

4. Simulation results

Table 1 and 2 present the average root mean squared error (RMSE) results for 500 simulations across different combinations of initial demand curve slopes, initial own-price demand elasticity, and time lengths. That is, for each combination of initial slope and elasticity assumptions, we simulate 500 known demand and/or supply shocks and observe market equilibrium price and quantity values for the assumed time length (e.g.

[5] Within the context of this simulation and because the actual demand shock is specified in step 2, the simulation of the new equilibrium price implicitly captures the supply shifts between periods. We assume that the demand and supply shifts are uncorrelated. However, if one assumes that the supply and demand shifts are correlated (i.e. the extent of the change in supply is somehow affected by the extent of the demand shift, or vice versa), the simulation analyses will not be affected because we would still know the exact extent of each curve's shift and identical simulated values would be used to test the accuracy of each index calculations. As such, for ease, we assume uncorrelated demand and supply shifts.

[6] The initial intercept value has only a scale effect on the empirical analyses. Thus, we arbitrarily set the value to 100.

Table 1. Root mean squared error of simulated demand shock index measurements, constant slope assumption.[1,2]

Index method	Initial elasticity (η_0)	Time series length (years)			
		5	20	35	50
Initial slope (β_0) -0.2					
Price index	-0.20	1,096.73*	4,874.90*	10,062.78*	18,959.44*
Quantity index		0.17*	0.64*	1.29*	1.61*
Price index	-0.60	11.17*	386.13*	3,103.96*	10,744.16*
Quantity index		0.54*	2.21*	8.00*	14.04*
Price index	-1.00	2.63*	786.01*	3,895.36*	6,243.61*
Quantity index		0.91*	4.91*	72.88*	145.64*
Price index	-1.40	2.47*	404.25	526.21	4,604.93
Quantity index		1.20*	135.32	158.18	493.65
Initial slope (β_0) -0.6					
Price index	-0.20	606.27*	3,357.74*	32,105.64*	72,412.85*
Quantity index		0.16*	0.57	1.06*	1.48*
Price index	-0.60	12.82*	707.94*	3,748.02*	5,615.82*
Quantity index		0.52*	2.02*	3.57*	94.24*
Price index	-1.00	2.04*	77.38*	848.20	2,746.84*
Quantity index		0.82*	4.08*	102.83	221.84*
Price index	-1.40	2.36*	82.56	443.90	12,292.48
Quantity index		1.17*	97.79	100.99	185.38
Initial slope (β_0): -1.0					
Price index	-0.20	2,624.71*	9,128.97*	11,041.26*	15,888.40*
Quantity index		0.18*	0.61*	1.05*	1.62*
Price index	-0.60	10.34*	363.26*	571.79	2,376.87*
Quantity index		0.55	1.93*	11.75	75.32*
Price index	-1.00	2.01*	197.21*	828.81*	3,467.44
Quantity index		0.88*	4.26*	25.37*	512.87
Price index	-1.40	2.36*	30.71	194.91	523.36
Quantity index		1.22*	43.33	251.81	668.72
Initial slope (β_0): -1.4					
Price index	-0.20	4,132.57*	8,253.18*	12,447.83*	17,303.38*
Quantity index		0.16*	0.59*	1.13*	1.82*
Price index	-0.60	11.02*	1,468.03*	1,414.00*	2,016.43*
Quantity index		0.50*	1.91*	13.74*	37.18*
Price index	-1.00	1.94*	105.88	1,152.03	3,797.46*
Quantity index		0.87*	62.73	124.29	157.36*
Price index	-1.40	2.46*	93.52	285.27	2,708.95
Quantity index		1.37*	13.69	345.10	4,545.90

[1] Values represent the average of 500 simulation iterations of the root mean squared error between the true simulated demand shock (relative to a base year t_0) and the demand shift estimated by each of the index approaches. The initial demand curve always has an intercept α_0=100 and the initial slope and elasticity as indicated in the table. Simulations were performed for different time series lengths to determine index performance for different time lengths away from the base year. Under the constant slope assumption, all demand curves (in the base period and all subsequent periods) have the same slope as the initial demand curve, while elasticity values differ based on the observed price and quantity combinations in period t.

[2] Statistically difference between the two RMSE values from zero to at least at a 10% level are indicated by an asterisk (*).

Table 2. Root mean squared error of simulated demand shock index measurements, constant elasticity assumption.[1,2]

Index method	Initial elasticity (η_0)	Time series length (years)			
		5	20	35	50
Initial slope (β_0) -0.2					
Price index	-0.20	3,412.70*	10,920.69*	25,326.93*	643,389.57*
Quantity index		0.29*	1.21*	2.29*	3.44*
Price index	-0.60	10.60*	1,214.82*	1,331.53*	2,278.56*
Quantity index		1.10*	5.32*	10.11*	41.71*
Price index	-1.00	4.32*	200.74*	571.33	1,685.87*
Quantity index		2.35*	42.96*	48.08	85.24*
Price index	-1.40	4.95*	99.27*	457.71	3,456.49*
Quantity index		3.84*	37.12*	197.41	230.12*
Initial slope (β_0) -0.6					
Price index	-0.20	2,816.93*	4,700.45*	26,293.18*	44,054.48*
Quantity index		0.30*	1.22*	2.15*	3.51*
Price index	-0.60	14.67*	808.09*	2,525.70*	6,158.60*
Quantity index		1.16*	5.56*	11.25*	63.80*
Price index	-1.00	4.45*	145.48*	1,478.72*	3,626.47
Quantity index		2.46*	20.09*	130.67*	231.89
Price index	-1.40	5.32*	227.23	613.90	14,573.57
Quantity index		4.29*	87.66	202.00	258.18
Initial slope (β_0): -1.0					
Price index	-0.20	1,795.49*	2,408.36*	12,624.92*	13,488.58*
Quantity index		0.27*	1.27*	2.46*	3.63*
Price index	-0.60	30.03*	1,836.34*	2,443.47*	5,756.15
Quantity index		1.10*	5.99*	47.56*	132.42
Price index	-1.00	4.93*	303.65*	1,263.83*	3,635.41
Quantity index		2.60*	14.11*	72.34*	127.98
Price index	-1.40	5.14*	53.40	775.12	1,073.75
Quantity index		4.36*	65.52	207.18	369.60
Initial slope (β_0): -1.4					
Price index	-0.20	3,734.89*	4,829.13*	13,357.15*	14,699.70*
Quantity index		0.30*	1.28*	2.27*	3.34*
Price index	-0.60	13.54*	1,139.02*	1,255.12*	3,661.53
Quantity index		1.05*	5.26*	10.27*	111.57
Price index	-1.00	4.87*	239.71	1,158.69*	2,320.18*
Quantity index		2.33*	56.48	91.17*	577.21*
Price index	-1.40	4.97*	183.57*	279.26	811.88*
Quantity index		4.33*	42.34*	359.62	4,145.21*

[1] Values represent the average of 500 simulation iterations of the root mean squared error between the true simulated demand shock (relative to a base year t_0) and the demand shift estimated by each of the index approaches. The initial demand curve always has an intercept α_0=100 and the initial slope and elasticity as indicated in the table. Simulations were performed for different time series lengths to determine index performance for different time lengths away from the base year. Under the constant elasticity assumption, all demand curves (in the base period and all subsequent periods) have the same elasticity as the initial demand curve, while slope values differ based on the observed price and quantity combinations in period *t*.

[2] Statistically difference between the two RMSE values from zero to at least at a 10% level are indicated by an asterisk (*).

for a time horizon of five periods, we simulate 500 five-period market time series). The average RMSE (with each RMSE representing the RMSE sum for the entire time horizon) are shown across the 500 iterations between the true demand shock and the estimated change in demand using the price and quantity index approaches. For example, an RMSE=1 would indicate that an index approach generated values that were one-unit higher or lower than the true simulated demand shift.

RMSE values presented in Table 1 and 2 are used for comparison purposes both between the price and quantity models and for each model across time periods, elasticity, and slope assumptions. Attempting to directly interpret the levels of RMSE values is less insightful because they are based on a simulation analysis and would be different if alternative starting values and market shock assumptions are used. Table 1 shows the results under the assumption that the slope of the demand curve remains constant across the entire length of a time series with elasticity values conditional on the observed price and quantity combination in each period of the time series. Table 2 presents the results assuming that the own-price demand elasticity is constant across the time series, but that demand slopes vary. We use *t*-tests to determine whether the difference between the average RMSEs are statistically different from zero; if so, then these values are bolded in Table 1 and 2.[7]

In general, the results indicate that for both indices and for both the constant elasticity and constant slope assumptions, the average root mean squared error increases with the length of the time period implying that, relative to the base period, the demand change measurement performance of both indices decreases. The degradation of the index predictions increase as the slope of demand functions decreases. However, the more important factor in this degradation is the elasticity estimate, because markets for which the initial demand is more inelastic (regardless of whether the elasticity is allowed to vary throughout the time series) have relatively lower errors across all slope assumptions. This suggests that the quantity index may be more suited for markets in which demand is relatively inelastic than the price index. The elasticities of demand for most broadly-defined agricultural commodities and food product categories are relatively inelastic.

The simulation results are also useful for comparing the two index methodologies. Table 1 and 2 show that in most cases, regardless of initial assumptions, the quantity index outperforms (often substantially) the price index, as measured by the magnitude of the average RMSE. The largest performance improvements are observed for demand curves that are relatively inelastic. However, even under the more elastic assumptions, the quantity index results in more accurate estimates of demand shifts than the price index. The only conditions in which the price index is superior are when the initial demand curve is relatively flat (i.e. the price elasticity of demand is relatively large) and when the initial equilibrium is on the elastic portion of a demand curve.

Additionally, the simulation analyses show that, regardless of the initial slope assumption, the quantity index provides more accurate measures of demand shocks for commodities that are relatively own-price inelastic. For example, assuming an own-price demand elasticity of η=-0.20, the quantity index predicts demand changes relative to a base period quite accurately, even when the index is calculated for market conditions that are 50 years from the base period. For more elastic initial elasticities, prediction errors are also reasonably small relative to the true index for estimates, but only up to 35 years from the base period. In general, the simulations help demonstrate that unless demand indices are used to examine products for which demand is relatively inelastic, estimating demand changes using distant base periods may be misleading because they can result in large errors. In those cases, resetting the base period to a more current year may be necessary to obtain more accurate demand shift estimates.

Finally, Table 1 and 2 show that, regardless of the assumption about whether demand shifts are parallel to the original demand curve (the constant slope assumption, Table 1) or are constrained to have the same elasticity throughout the simulation (the constant elasticity assumption, Table 2), the quantity index is almost

[7] Because we are comparing central tendencies of large-number simulated distributions, we assume that the distributions converge to Student's *t* and can, therefore, be standardized and compared using *t*-tests.

always more accurate than the price index. The accuracy of the quantity index is robust regardless of how one models demand curve shifts.[8]

5. Meat market applications

The quantity index can be easily applied to four meat products (beef, pork, lamb, and poultry), which represent a classic set of products for which demand indices have been widely used. For the four meat products, annual consumption (in pounds per capita) and nominal retail price (in cents per pound) data between 1980 and 2014 are obtained from the Livestock Marketing Information Center. Nominal prices are converted to real terms using the chain-weighted 1982-1984=100 consumer price index.

For each of the products, we obtain own-price demand elasticity information from published studies. When available, we used long-run elasticity estimates because demand indices measure changes over relatively long time horizons. In cases where we were able to obtain more than one elasticity estimate from the extant literature, we used simple averages of those estimates in our analyses. Because approximately one-half of US lamb consumption consists of imported products, we use an average of reported imported and domestic long-run demand elasticities. Table 3 presents the elasticities values (and associated sources) to develop four food demand indices.

Figure 3 presents a visual comparison of the two competing demand indices for the four meat products and Table 4 shows summary statistics of the two approaches. The price indices, presented in Equation 1, reflect those that are currently published and used by industry participants. The alternative quantity index approach is calculated following Equation 2. Figure 3 shows that relative to 1980, both indices for beef, pork, and lamb products illustrate similar declining demand trends. However, for each of these products, the price index approach suggests substantially greater reductions in demand through the 1990s than that indicated by the quantity index. For example, the price index suggests that beef demand declined 50% between 1980 and 1995, before rebounding to an index value of 58 in 2014. By comparison, the quantity index indicates a more gradual (and, we suggest, more realistic) decline over the 35-year period, ending with a 2014 value of 67. Figure 3 and Table 4 show that similar downward biases in the inverse-demand function index are also evident in the pork and lamb markets.

[8] We acknowledge that the own-price elasticity of demand may change over time, which would likely affect the accuracy of demand change estimates produced by either the price or quantity index. Ultimately, the accuracy of both models depends on the accuracy and availability of elasticity estimates. However, because we show that the quantity index method is more consistent with a neoclassical representation of demand shifts and empirically outperforms the price index regardless of the demand curve's elasticity or shape assumptions, the extent of the potential error related to time-variant elasticities will be smaller when using the quantity index approach.

Table 3. Sources of estimated own-price demand elasticities and values used for index calculations.[1]

Product	Source	Elasticity estimate	Value used for index calculation
Beef	Mutondo and Henneberry (2007)	η_{LR}=-0.71	$\bar{\eta}_{beef}$ = -0.54
	Tonsor *et al.* (2010)	η_{LR}=-0.42	
	Tonsor and Olynk (2011)	η_{LR}=-0.49	
Pork	Kaiser (2012)	η_{LR}=-0.66	$\bar{\eta}_{pork}$ = -0.66
Lamb	Brester *et al.* (2007)	Domestic, η_{LR}=-1.11	$\bar{\eta}_{lamb}$ = -0.87
		Imported, η_{LR}=-0.63	
Poultry	Eales *et al.* (1998)	η_{LR}=-0.52	$\bar{\eta}_{poultry}$ = -0.52

[1] Long-run own-price demand elasticities are used, except in cases when it was not possible to determine whether the estimate was long- or short-run.

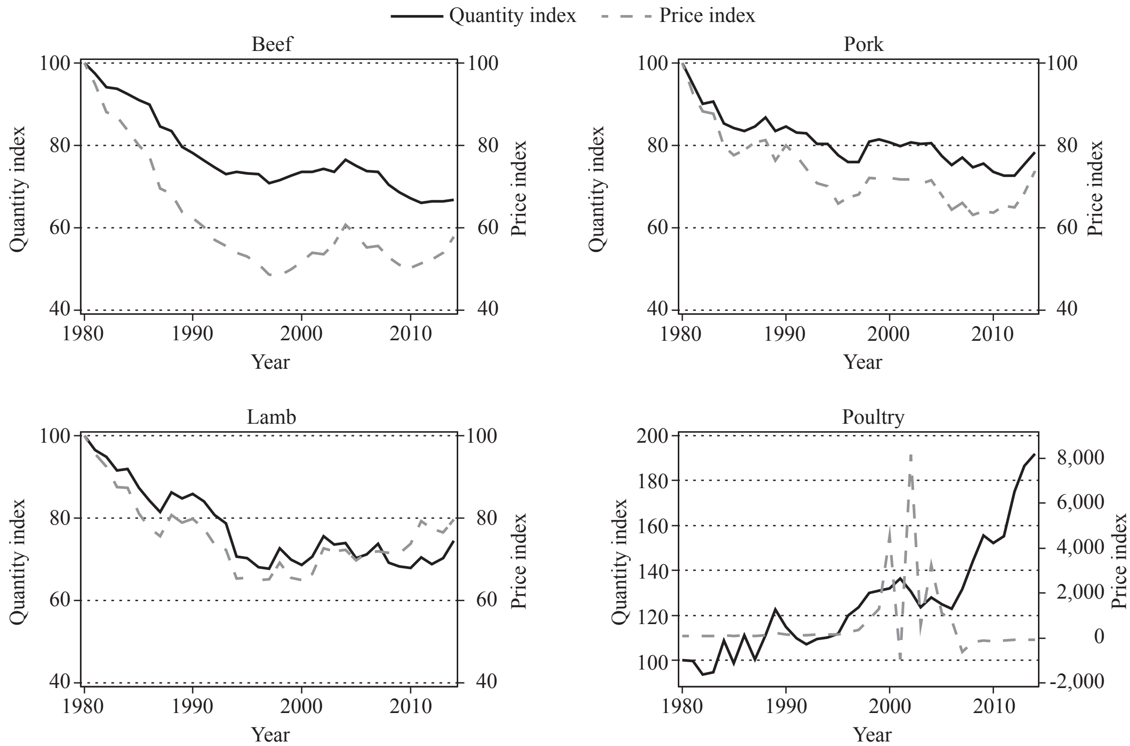

Figure 3. Meat demand indices using quantity and price index approaches. In the 1980 base year, all index values are 100. The left-side vertical axis corresponds to the quantity index (solid line) and the right-side vertical axis corresponds to the price index (dashed line).

The comparison of the two index approaches also shows that demand shifts based on the price index are much more volatile than those provided by the quantity index approach. While this was initially revealed in the simulation analyses, Table 4 characterizes these increased volatilities for the four meat products. For example, the range of the price index values is higher than that of the quantity index values across all four meat products. Additionally, the coefficient of variation for the price index is statistically greater than the quantity index for beef, pork, and poultry products, while there is no statistical difference between the two for lamb.

Both Figure 3 and Table 4 show that the price index volatility is particularly evident in the poultry market. The quantity index presented in Figure 3 suggests that the demand for poultry products increased gradually between 1980 and 2014 and indicates an approximate doubling of demand over the 35-year period. However, attempts to estimate demand changes using the price index yields nonsensically large and small values throughout most of the 1990s and 2000s (with index values as high as 8,173 and as low as -951) before finally suggesting that poultry demand has *declined* 61% by 2014.[9]

Finally, two additional comparisons between the competing index approaches are useful. First, while Table 4 shows that the magnitude of demand changes and volatility of shifts are sensitive to underlying calculations, current practitioners employing the price index approach will be pleased to note the two approaches generally yield the same directional conclusions. Nonetheless, given the use of demand indices in longer-term assessment of demand patterns, the magnitude of changes is obviously key to accurate assessments.

[9] For robustness purposes, we also investigate demand indices for four energy commodities – gasoline, diesel fuel, electricity, and natural gas. The price index approach generates nonsensical estimates of changes in demand for electricity and diesel fuel similar to what is observed for the poultry sector.

Table 4. Summary statistics of calculated indices for meat products.[1]

	Index method	Mean	Range	CV	Similar direction	Number years with identifiable shifts	Correctly predicted identifiable shifts
Beef	Price index	61.96	51.61	22.82	0.77	12	1.00
	Quantity index	77.42	33.96	12.31			1.00
Pork	Price index	73.74	36.83	11.77	0.80	10	1.00
	Quantity index	81.20	27.35	7.52			1.00
Lamb	Price index	75.63	35.10	11.59	0.86	13	1.00
	Quantity index	77.56	32.29	12.19			1.00
Poultry	Price index	596.72	9,125.06	275.36	0.91	26	0.88
	Quantity index	125.78	97.91	19.50			1.00

[1] Range: difference between the maximum and minimum value. CV: coefficient of variation, calculated as the ratio of the standard deviation to the mean times 100. Similar direction: percentage of times that both the price and quantity index indicate the same between-year directional change in index values (e.g. both indices increase or decrease between periods t and t – 1). Number of years with identifiable shifts: how many periods between 1980 and 2014 observed equilibrium price and quantity either both increased or both decreased (an indication of a demand shift). Correctly predicted identifiable shifts: proportion of years when a demand shift was identifiable, and an index correctly predicted a correct upward or downward demand shift.

Table 4 presents the results of another directional consistency check for the two indices. We consider the proportion of times that each index correctly predicts an upward or downward demand shift in years when the direction (but not magnitude) of a demand shift is identifiable from realized price and quantity market data. That is, if both the observed equilibrium price and quantity between years t and t – 1 increases (decreases), it is necessarily the case that demand shifted upward (downward) by some amount. We use these specific market conditions to determine whether the competing indices are able to predict directional demand shifts. Table 4 shows that for beef, pork, and lamb, both indices correctly predict demand shift directionality. However, in the case of poultry, only the quantity index correctly predicts every positive and negative demand change in years when those the direction of those changes could be directly identified.

6. Implications and conclusions

Food research and policy has increasingly shifted from a focus on farm-level productivity to other concerns (Alston *et al.*, 2009). Of particular interest has been changes in consumer demand and food consumption behavior. Agricultural commodity producer and marketing industry groups – especially those associated with meats – have invested substantial resources into nudging consumer demand for the retail food products associated with an industry group's commodity – primarily through promotion and research and development efforts. Evaluating the efficacy of such efforts has generally hinged on appropriately measuring the extent to which demand changes for specific commodities, rather than simply observing changes in consumption behaviors that may be driven by supply-side dynamics.

Accurately analyzing the effectiveness of these initiatives is critical for assessing the cost-benefit tradeoffs associated with implementing any given demand-altering strategy. In the US meat industry, demand indices have been the primary tool for evaluating the success of consumer demand-focused initiatives. The approach has also been used to analyze the impacts of government country-of-origin labeling policies (for example, see Brester *et al.*, 2004). The propensity with which the price index approach to measuring demand changes has been used in the past and increasing government policy and industry initiative focus on consumer behavior requires that a technique be used to accurately measure the economic impacts of these efforts.

The impetus for this research was initiated by the realization that the price index approach generated unrealistically large (both positive and negative) estimates of annual changes in the demand for poultry in certain years. This particularly odd result occurred because, as is the case for many food products, poultry has a relatively inelastic demand and the market experienced rapid and large structural changes as a result of technological innovations. In such markets, prices can be more volatile (as they adjust to clear markets that are rapidly evolving), which causes the price index to also become highly unstable. The reason is that original index is based on differences between observed and expected prices. Hence, because the index accounts for and inherently aggregates predicted demand changes in preceding periods, using the price index to assess market conditions in rapidly evolving markets can eventually lead to explosive estimates such as those observed in the poultry market.

In more stable markets, such as those for other meat commodities, the price index does not generate any obviously unrealistic estimates of demand changes. Nonetheless, we show that our quantity index approach provide more accurate estimates of demand changes. Our simulation analyses show that when demand-side industry campaigns are evaluated using existing index methods, the results may be significantly over- or under-estimated. These inaccuracies can contribute to potentially costly and inefficient uses of investor and stakeholder resources, lead to ineffective growth strategies, and cause industry groups to incorrectly assess marketing and research efforts. Our work rigorously evaluates a traditional demand index approach and an easily implemented alternative that is more consistent with neoclassical theory. We show that this alternative quantity index should always be used to make such assessments rather than the existing price index approach.

In the future, the continued promise of collecting and using higher frequency, product-specific, and/or 'big' data could provide the opportunity to apply and extend our methodology in order to provide more detailed understanding of changes in market demand conditions (Capps, 1989; Brester and Wohlgenant, 1991; Nayga and Capps, 1994; Brooks and Lusk, 2010). In these cases, it remains unclear whether the increased amount and detail of the data may substantially reduce remaining inaccuracies. Furthermore, our research could be used as a foundation for a parallel effort to better identify changes in supply, rather than quantity supplied, that would also assist academic and industry practitioners in more accurately characterizing changing market environments and assessing issues such as changes in agricultural productivity (Pardey *et al.,* 2013).

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