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in Agricultural and Resource Economics

Research
Paper
2014-03
Fall
2014

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Stratifying the Staircase: Residential Water User Segmentation Under Increasing Block Rate Pricing Structures

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I. Abstract

Improvements in residential water efficiency and increasingly stressed water supplies continue to reduce the margin of error in which water utilities are able to operate. Expectations for increased temperatures and the occurrence of extreme weather events increases the need for water utilities to be able to adapt operations to account for changes in the future. This article introduces a probabilistic technique for segmenting single-family residential water users into consumption groups based on consumption behavior and price thresholds imposed by an increasing block rate pricing structure. Strategic segmentation of users allows for more precise analysis of exogenous influences on consumption behavior..

II. Introduction

Changes in weather patterns as a result of climate change put stress on water supplies, increasing the need for water utilities to adapt the way they plan for meeting customer demand and maintaining financial viability. Water utilities operating on a limited revenue stream are expected to encourage water conservation while keeping water costs affordable. Over the last several decades, many water utilities have experienced a decreasing trend in water consumption, making it increasingly difficult to generate sufficient revenue from their users to cover the high capital costs associated with running a water utility (Tiger, Hughes, & Eskaf, 2014). Though the decrease in consumption is a step toward water conservation and preserving supplies for the future, the rapid and unexpected rate at which consumption is decreasing limits the ability of utilities' to cover long-run capital costs and plan for the future.

This article employs a detailed panel of household level water use data over a 48 month period to obtain a better understanding of water demand in the Tucson, Arizona metropolitan

area. This detailed panel of household level data is linked to weather and household characteristics on an observational basis, providing one of the most detailed data sets available in the literature. The sample period covering July 2007 and ending in June 2011 is of interest because it corresponds with the burst in the American housing bubble and subsequent recession. During this period, single family residential service connections for water in Tucson fell from a consistent two decade growth rate of over two percent to nearly zero.

This article introduces a new way of segmenting users into different groups based on behavior and the institutional rules imposed by increasing block rate pricing structures. Segmenting households based on consumption behavior using probability principles provides a useful way to explore the validity of imposing an increasing block rate structure by testing for differences in price and income response between groups. The price elasticity results obtained for each user segment can be used to set prices for each block strategically to encourage conservation while helping the water utility reach its revenue goals (Klawitter, Colby, & Thompson, 2014).

This article also introduces an alternative measure of household income, intended to provide a more precise income value for each household in the sample of users. Using this new income measure, we find that changes in income have larger magnitudes of impact on water use for consumers in the highest water use segment. Users with higher incomes were also expected to be placed in higher water use blocks.

In addition to the model-specific contributions of this article, Tucson, Arizona is an ideal area for analyzing water demand and the uncertainties facing water utilities. The arid climate, intense regional competition for water, and strong recession effects highlight challenges facing

utilities in many areas of the world. In addition to Tucson, several large metropolitan areas in the arid Southwest—Phoenix, Las Vegas, Los Angeles, and San Diego—rely at least in part on Colorado River water to meet residential water demands. Declining levels in Lake Mead, the primary Colorado River reservoir serving these lower basin cities, shows the impending threat of water shortage and the importance for water providers to be proactive in addressing issues of water management.

In addition to the strong regional competition for water, Tucson has a large population of water users who depend solely on groundwater and Colorado River water delivered via the 336 mile Central Arizona Project Canal (CAP). Tucson Water provides water to a population of 709,000 people, through approximately 226,000 service connections within its service area. These customers consumed approximately 136,000 acre-feet (AF) of water in 2008.

Since 2008, both total single family residential (SFR) water use and per-service SFR water use has been declining rapidly. The decline in total and per service use is shown in Figure 1 (a) and (b), respectively. Determining the contributing factors to the decrease in use is important in order to achieve more accurate projections of future demand. The long-term decrease in per-service use, shown in Figure 1(b), is likely a result of more efficient water using appliances and fixtures becoming available over time. The decreasing trend in variability between summer peak and winter trough also indicates that water use is becoming more efficient over time. The sharp decline in total use, shown in Figure 1(a), starting around 2007 is likely due to changes to the housing market and economic environment that occurred during the recession. Understanding the contributing factors to these changes in water use, as well as

the effects that each of the contributing factors has on water use trends is important for the long-term planning of the water utility.

[Figure 1]

A recent summary published in the Bulletin of the American Meteorological Society cites that Colorado River Stream Flows are expected to decline by between 6% and 45% mid-century (Vano, et al., 2014). The two main reservoirs on the Colorado River, Lake Mead and Lake Powell, are expected to store reduced volumes over the coming decades (Gammage, Stigler, Clark-Johnson, Daugherty, Hart, & ., 2011). Tucson Water's access to Colorado River water is made even more uncertain due to Arizona's Central Arizona Project (CAP) entitlement being a junior rights holder for receipt of Colorado River water. While the CAP has a plan for dealing with shortages that gives priority to municipal recipients of CAP water during shortages, in extreme shortage cases, even high delivery priority recipients such as Tucson Water could feel reductions (CAP, 2011). As supplies become increasingly stressed and the overall variability in demand decreases, more precise demand estimation techniques will become more important for informing water resource operations.

III. Literature Review

The residential water demand literature generally focuses on single-family residential customers because they account for the largest proportion of consumption in most metropolitan areas. The disaggregation of water user data for demand estimation allows for household-specific variation to be accounted for in demand modeling. This reduces omitted variable bias in estimation by allowing econometricians to include variables that account for

user heterogeneity. Though the benefits of disaggregated user data are great, more often than not, data sets available for residential water demand analysis are aggregated at some level higher than the individual household and produce results that do not capture user heterogeneity.

Explanatory Variable Choice

Explanatory variables in water demand models can be broken into two main groups: 1) factors under the utility's control and 2) factors outside of the utility's control (Kenney, Goemans, Klein, Lowrey, Reidy, & ., 2008). Factors under the utility's control include pricing structures and demand management strategies such as conservation incentive programs, while those outside the utility's control are variables such as weather, economic, household and demographic characteristics.

One factor within a utility's control is pricing. Researchers take various approaches to estimate price elasticity of demand, which is inherently complicated for two reasons; first, most utilities in the western United States use increasing block rate (IBR) structures for water pricing. An IBR is a pricing schedule that allows the water utility to charge users a per-unit price for water that increases as consumption increases (Waters, Klawitter, Paul & Hamilton 2014). The second complication with estimating water demand comes from the lack of information the average customer has regarding their marginal price at any given moment (Nataraj & Hanemann, 2011). This lack of information comes from both the non-constant marginal price of an increasing block rate structure as well as the way water utilities typically track water use in the western US. Water consumption is typically monitored by a single meter located on the

exterior of a home, hidden under a heavy steel plate, making it difficult for users to track water use until they receive their water bill.

In addition to the lack of knowledge of water use until the billing period is over, many water utilities have bill start and end dates that vary each month—the bill length often depending on a manual meter reader's schedule. Having a billing cycle that varies in length when the commodity charge is based on volume consumed within that period can make the marginal price of water vary to consumers without any change in consumption behavior, in turn sending conflicting price signals to the user.

In addition to the mixed price signals, the varying length of billing periods makes it so billing cycles may start on a different day each month. Having billing cycles start on different days each month makes it difficult for even the most interested consumers to calculate their marginal price at any given point during the cycle (Foster & Beattie, 1979; Nataraj & Hanemann, 2011).

The lack of information the consumer has on the marginal price of water at the time of consumption has led some water demand researchers to argue that consumers respond to the average price of water found on their water bill (Foster & Beattie, 1979; Dalhuisen, Florax, de Groot, Nikkamp, ., & ., 2003). Other researchers offer results that suggest that water consumers respond to the marginal price that they expect to face, based on where they think they are in the block rate structure (Nataraj & Hanemann, 2011). Several studies have found evidence that water users do respond to marginal price (Nataraj & Hanemann, 2011; Olmstead, Hanemann, & Stavins, 2007; Hewitt & Hanneman, 1998; Klaiber, Smith, Kaminsky, & Strong, 2010). The complex pricing structure has also has given rise to the argument that an income adjustment

should be made for users consuming in blocks other than the lowest (Nataraj & Hanemann, 2011; Hewitt & Hanneman, 1998). One study from Tucson in the late 1980's found that models using average price have strong explanatory power when incomes are higher relative to price. However, as water prices increase relative to income, marginal price is the preferred price value for estimation (Billings & Day, 1989). Regardless of the form that the price variable takes in an econometric study, the literature consistently finds that urban water demand is price inelastic (Dalhuisen, Florax, de Groot, Nikkamp, ., & ., 2003).

One meta-analysis of price elasticities for residential water demand found that elasticities range from $-.02$ to some outliers as high as -3.33 with an average estimated value of $-.5$. This analysis also found that elasticities are larger in absolute value when increasing block rates are implemented in lieu of a constant marginal price (Espey, Espey, & Shaw, 1997). The relatively low elasticities generally found are attributed to both the lack of knowledge of price at the time of consumption as well as the small size of the monthly water bill relative to income.

In addition to understanding how consumers respond to prices, it is important for utilities to understand how users in different demographic categories use water. Adding information about user demographics to a demand study accounts for customer heterogeneity and reduces the influence of omitted variable bias of the study while improving the understanding of how water use responds to demographic changes.

Studies have linked demographic information to households to compare use in different demographic categories (Kenney, Goemans, Klein, Lowrey, Reidy, & ., 2008; Ray, 2012).

Another study focuses on water users in Santa Cruz, California finding that elasticities for water

users in the highest tier of the increasing block rate structure were lower (in absolute value) than those of users in the low and middle tiers (Nataraj & Hanemann, 2011). The authors attributed this to an income effect that outweighed the price effect for the highest tiered water users. Nearly every water demand study discusses the importance of including an income variable in water demand models (Agthe & Billings, 1980; Brookshire, Burness, Chermak, & Krause, 2002).

Beyond the demographic variability of households, it is also important to account for differences in physical characteristics of housing. Square footage of the home is often found to have a significant positive relationship with water consumption (House-Peters & Chang, 2011; Chang, Parandvash, & Shandas, 2010; Balling, Gober, & Jones, 2008; Harlan, Yabiku, & Brazel, 2009). In arid regions, a large portion of residential water use is dedicated to maintaining landscapes on the exterior of the homes, variables measuring outdoor area, normalized difference of vegetation index (NDVI) and pool size are often included (Wentz & Gober, 2007; Balling, Gober, & Jones, 2008; House-Peters & Chang, 2011; Tinker, Bame, Burt, & Speed, 2005).

Because outdoor attributes of a home influence water demand, it also follows logically that weather variables influence water demand. Weather factors are especially important in determining the amount of water used for irrigation (Tinker, Bame, Burt, & Speed, 2005; House-Peters, Pratt, & Chang, 2010; Balling, Gober, & Jones, 2008). The literature consistently finds that when weather is hotter and drier, water demand increases.

Though the literature is consistent on the importance of weather factors in demand, no consensus exists on which measures of temperature and precipitation are optimal. One meta-analysis of more than 20 water demand studies finds that temperature, precipitation and wind

speed were the most common weather variables in the demand models examined (House-Peters, Pratt, & Chang, 2010). Beyond using a simple precipitation measure variable, several studies in the southwestern U.S. have found that breaking precipitation variables into summer and winter precipitation accounts for the seasonal nature of outdoor water uses.

Defining the precipitation variable in a seasonal manner is especially useful in Arizona and other southwestern states due to the difference between summer “monsoon” rains and winter rains. Monsoonal rainfall often occurs in intense bursts and is spatially heterogeneous, creating more flooding and run-off than winter rains (Woodard & Horn, 1988; Young, 1973; Billings & Day, 1989).

Econometric Specification

Though most of the literature uses similar explanatory variables to estimate water demand, there is a large variation in the types of statistical models used. The model choice is generally dependent on the fundamental questions the researcher addresses and the type of data that is available to the researcher. Figure 2 shows an overview of the different types of models discussed in the remainder of this section.

[Figure 2]

Analysis of residential water demand is done for both the aggregate and user levels. As statistical software has become more advanced, disaggregated data has become preferred to aggregated user data so that models can capture user heterogeneity. Data are generally organized either as a time series or a cross-section, or a combination of the two.

Time series models are useful for forecasting water use, but cannot capture the effect of user attributes on consumption. Cross-sectional estimation allows researchers to observe the

effects of user heterogeneity, but have limited forecasting ability. Panel datasets tend to be preferred for long-term planning because they allow researchers to account for both the temporal and cross-sectional variations that influence water use.

The econometric models used for estimation with time series data varies widely between studies. Ordinary least squares (OLS) and feasible generalized least squares (FGLS) regression techniques have been used in studies focusing on simple short-term forecasting (Agthe & Billings, 1980; Gutzler & Nims, 2005). OLS and FGLS are also used often in time series studies to estimate the effects of changes in climate and demographics (Woodard & Horn, 1988; Wong & Chen, 2010).

When autocorrelation is significant in time series data, many researchers choose autoregressive integrated moving average (ARIMA) models to estimate demand (Praskievicz & Chang, 2009; Adamowski, 2008). ARIMA models account for autocorrelation and assume current use is dependent on past use, making ARIMA models also preferable when the availability of data for explanatory variables is limited.

The studies using strictly cross-sectional data focus heavily on spatial differences, so models that integrate geographic techniques are often chosen. Demand models that use geocoded data sets used spatially explicit OLS regressions and geographically weighted regressions (GWR) (House-Peters, Pratt, & Chang, 2010; Shandas & Parandvash, 2010; Wentz & Gober, 2007; Balling, Gober, & Jones, 2008).

Other researchers have estimated price elasticities under the non-constant marginal pricing of an increasing block rate structure. The three most common models that account for the piecewise linear budget constraint resulting from the IBR are instrumental variables,

multiple stage least squares, and discrete-continuous choice (DCC) maximum likelihood models (Hewitt & Hanneman, 1998; Jones & Morris, 1984). The DCC model accounts for the piecewise linear budget constraints resulting from non-constant marginal pricing (Hewitt & Hanneman, 1998; Olmstead, Hanemann, & Stavins, 2007). A recent study using a DCC model to estimate water demand found that though a DCC model estimates demand in the most theoretically sound manner of modeling the consumption decision of residential water users billed using an IBR, the resulting elasticity estimates are not significantly different from those of prior studies which estimate elasticity using simpler estimation techniques (Olmstead, Hanemann, & Stavins, 2007; Olmstead S. M., 2009). Additionally, the assumption of perfect information at the time of consumption for residential water users can be far from accurate depending on the billing techniques implemented by a water utility (Billings & Day, 1989). The DCC models estimated for water use give cross-sectional estimates and do not account for changes in use over time.

In addition to the time series and cross-sectional studies, other studies use panel regression techniques. One popular panel estimation technique is the fixed effect panel model, which averages out the time-invariant unobserved effects from the model (Kenney, Goemans, Klein, Lowrey, Reidy, & ., 2008). Using a panel model allows for the inclusion of variables that capture both the time and cross-sectional variations present in a sample. The averaging-out in the FE model produces unbiased and efficient parameter estimates for each of the independent variables (Kenney, Goemans, Klein, Lowrey, Reidy, & ., 2008; Polebitski & Palmer, 2010).

Following a similar logic to a fixed effects demand model, a random effects instrumental variable (RE-IV) panel model can be used to estimate demand, and may be preferable to a fixed effects approach for several reasons. Random effects models allow for the inclusion and

estimation of parameters of time invariant explanatory variables. Random effects models also have smaller expected standard errors than fixed effects models as well as unbiased parameter estimates as long as the omitted variables are uncorrelated with the explanatory variables (Wooldridge, 2010). Random effects models also allow for out-of-sample prediction, which can be useful for inference both cross-sectionally and over-time. Using instrumental variables to estimate price for water addresses the simultaneity issue introduced to the demand models by the non-constant marginal price of an IBR (Jones & Morris, 1984).

This literature review of water demand studies facilitated choice of variables and most suitable model specification for demand estimation under this project. The model used in this project is a random effects instrumental variable model, which is preferable to other models discussed because it accounts for time and cross-sectional variation in the data, accounts for the simultaneity introduced to demand estimation by the non-constant marginal price for water and allows for out of sample inferences.

IV. Description of Data

Single Family Residential Water Usage Data

The water use data for this analysis are comprised of single family residential (SFR) billing records from Tucson Water. Household level records for all SFR water users within the Tucson Water service area were obtained for the years 1997 through 2012. This dataset only contains residential customers who are individually metered for water consumption; this does not include apartment complexes and multiple households receiving water from the same meter. The data does not account for varying numbers of individuals within a single household due to availability.

Tucson Water bills its customers on an asynchronous billing date and cycle length, meaning that the day the customer receives their bill and the length of time that a bill covers varies, because meters are read manually. The data received from Tucson Water shows that over the period 98% of bills ranged in length from 27 to 35 days. Longer billing periods naturally imply higher water use and Tucson water does not standardize user bills before determining marginal prices according to the increasing block rate schedule. Because the billing cycle length varies, the marginal price for water is dependent on both the use pattern of a household as well as the length of billing cycle. To separate the effects of water use variation due to billing cycle length from the actual household behaviors influencing water use, the household observations were standardized as follows.

$$\text{Standardized Use}_{it} = \frac{\text{total usage}_{it}}{\text{billing days}_{it}} \times 30 \text{ days} \quad (1)$$

This standardization allows a comparison of consumption behavior across billing periods and households. Removing the billing cycle length effect from the usage data allows the true relationship between the explanatory variables and the dependent variable to be shown in our model (Nieswiadomy & Molina, 1988).

Though the water use data covers a 16 year time span, we focus on a shorter time period for this analysis: July 2007 through June 2011. The shorter sample period was selected for two reasons. First, we have a very detailed cross-section of user data with a large rate of new homes being built over the period. In order to perform a panel analysis with a balanced sample, each year that we chose to add to the sample, would require us to systematically leave out information on users who live in homes that were built after the first period included in the sample¹. Thus a limited number of recent years is desirable.

The second reason this sample period was chosen is because Tucson Water implements changes in their rate structure at the start of each fiscal year, beginning July 1st. Having a 48 month sample allowed us to observe four different price schedules to see how users respond to changes in price. The resulting balanced sample of single family residential water users in the 48-month period consists of 118,950 households in the Tucson Water service area. Due to the economic downturn that occurred during this period, the water service connection growth rate was very low. As a result of the low growth rate, the number of new households omitted from the sample is very low.

We segmented the households into four groups based on usage patterns that coincide with the thresholds for each of the four blocks in Tucson Water's increasing block rate structure (Figure 5a). The segmentation was conducted under the hypothesis that users who consistently find themselves consuming in the highest block likely respond differently to price and exogenous changes than people in the lower blocks. The probability distribution of usage over the sample period was estimated; using a two-step process users are placed into their respective segments. These segments form a partition of the sample space.

The decision rule for segmenting the consumers utilizes a two-step approach to calculate the probability that a user is truly representative of a given block segment. The first step was to estimate the probability distribution of total monthly usage during the period, which we did using a parametric gamma distribution with $\hat{\alpha}=1.03$ and $\hat{\beta}=11.1$ (Figure 3). The parameters for the gamma distribution were estimated using the population distribution of household use during the sample period with all cross-sectional and time series observations included in the estimated distribution. Using the estimated Gamma distribution, the probability

of a user consuming in each of the four blocks at any given time during the sample period was estimated (i.e. let U equal the probability of consuming in a given block during the 48 month period), the results are shown in Table 1.

[Figure 3]

[TABLE 1]

Since we are ultimately interested in the number of times a household must consume in a given block to be considered a 'representative user' of a block, the second step in the segmentation process can be thought of as a Bernoulli trial (a user either consumes in the k^{th} block or they do not). Because we are interested in calculating the probability of multiple Bernoulli trials, it is appropriate to use the binomial distribution for calculating the number of times a user must consume in a given price block during the sample period to be considered a non-random event.

The probability of consuming in block K , calculated using the gamma distribution above, is used as the probability of the event occurring (i.e. a household consumes in block k) for the Binomial distribution, with $n=48$. Let X = the number of times a household consumes in block K .

The decision rule using the binomial distribution is that a consumer needs to consume in a block enough times that the probability of that event occurring is as close to 1 in 100 as the discrete distribution allows. The results of the Binomial calculations are shown for each of the four blocks in table 2.

[TABLE 2]

Because we assign households to segments based on total monthly use, and the probability of consuming in a block decreases as the usage requirement for segmentation into that block increases; the segments contain fewer households as the block increases². Random samples of 5,000 cross-sectional observations are pulled with replacement from the segmented population. After sampling duplicate household observations are removed. Table 3 shows the number of households placed in each mutually exclusive segment and the samples corresponding to each.

[TABLE 3]

Segmenting users based on consumption behavior and institutional constructs created by non-constant marginal pricing allows for strategic analysis of user response to price and other exogenous variables that may vary with quantity consumed. Using univariate probability principles to segment users based on restrictions imposed by the water utility, rather than other separation techniques like quantiles or other order statistics, allows for results that are more relevant to the market in which demand is being estimated. Further, inferences from the demand models estimated for each user segment allows utilities to make decisions, such as where to set the marginal price and threshold of a given price block (Klawitter, Colby, & Thompson, 2014).

Figure 4 below shows the average use for each of the four segments over the sample period. Two patterns emerge in Figure 4 supporting the hypothesis that households in each of the segments use water differently and may respond differently to exogenous shocks. The first

pattern is that the seasonal variation differs in trend and magnitude for each segment. The second is that the average total use for each segment increases significantly as the block coinciding with that segment increases. Both of these results further support the decision to segment the households prior to demand model estimation.

[Figure 4]

Estimating Average Price Using Instrumental Variables

Given the asynchronous billing cycles employed by Tucson Water, users do not have clear information on marginal price when making water consumption decisions. Rather than assuming that consumers can gauge, at the time of consumption, where they lie on the marginal price schedule, we assume that consumers perform a more basic utility maximization process using an average price per unit that can be easily calculated by looking at a water bill. Figure 5(a) shows the marginal price for water as defined by the increasing block rate schedule for water in Tucson during the sample period. Figure 5(b) shows the average price for water determined by all water related fees included on a Tucson Water bill. The initial steep decline in average price illustrated in Figure 5(b) shows the effect of including surcharges in the price for water; users who use very little water see a very high per unit average price for water that decreases as consumption increases up to the first block threshold between blocks one and two.

{Figure 5}

Because of the increasing block rate structure, water prices are dependent on quantity consumed which causes a simultaneity issue for demand estimation. A Durbin-Wu-Hausman

test was performed to test for the presence of simultaneity introduced by the non-constant marginal price of the IBR³. The test indicates that the simultaneous nature of price level has a significant impact of the parameter estimates for average price and, therefore, it is appropriate to use a two-step instrumental variable approach to correct for the specification error.

To address the effects of simultaneity, a two-step instrumental variable (IV) approach was used to estimate the average price per unit. Using an instrumented average price rather than the observed average price removes the correlation between average price and the idiosyncratic error of the demand model (Jones & Morris, 1984).

In order to estimate instrumental average price per unit, the following random effects panel model was estimated.

$$AP_{it} = \beta_0 + \beta_1 IV_{1iy} + \beta_2 IV_{2y} + \beta_3 IV_{3y} + \beta_4 IV_{4y} + \beta_5 IV_{5y} + \beta_6 IV_{6y} + \beta_7 Sewer Fees_{iy} + u_i + \varepsilon_{it} \quad (2)$$

Where:

IV_{1iy} = The total cost of water for each household $i=1,..n$, in year $y=2007,..2011$

IV_{2y} = The difference in real price between block 2 and block 1 in year $y=2007,..2011$

IV_{3y} = The difference in real price between block 3 and block 1 in year $y=2007,..2011$

IV_{4y} = The difference in real price between block 4 and block 1 in year $y=2007,..2011$

IV_{5y} = The difference in real price between block 3 and block 2 in year $y=2007,..2011$

IV_{6y} = The difference in real price between block 4 and block 2 in year $y=2007,..2011$

$Sewer Fees_{iy}$ = The sewer fees for each household $i=1,..n$, in year $y=2007,..2011$

u_i = the individual-specific error associated with the panel regression

ε_{it} = the error in the model associated with measurement error

The pricing structure variables included in this estimation follow the same logic as the models estimated by Jones and Morris (1984), Nieswiadomy and Molina (1988) and Kenney et al (2008). All instrumental variables chosen, with the exception of IV_1 , are set by the utility and thus should not be correlated with the error term of the demand equation for household water

use. Though IV_1 is correlated with total annual use, it should not be correlated with the variation in household water use in each period of a given year.

Using equation (2), the random effects panel models were estimated for each of the four block user segments. Table 4 shows the results from model estimation. All four of the block segment models are considered significant overall by the large Wald test statistic. In addition to the models' overall significance, each of the seven instruments included in the model are considered significant at the most stringent levels of significance. The overall significance of both the model and each variable indicates the IV estimates for average price are appropriate for estimating water demand.

[Table 4]

Income Data and Construction of Income Variable

Income is expected to be relevant as consumers choose water consumption levels (Nordin, 1976; Taylor L. D., 1976). Some past studies have used individual assessed home values as a proxy for income, while an equal number of studies have used census estimates at the census block or tract level. Though either income estimate seems reasonable given the data that is typically available for empirical analysis, neither is an ideal estimate for actual income. The assessed value of a home can change with market conditions and is probably a better estimate of household wealth than monthly income. One positive attribute of assessed value is that it varies on a yearly basis and it is available at the household level. Census estimates are probably a better approximation of income than a home's assessed value, but are only

estimated periodically and do not take into account the income heterogeneity within a census block or tract.

To get the best possible income estimates, we develop an alternative income measure calculated using both the census income and the assessed value of a home. To estimate income for each household we first obtained the estimated median income for each census tract in Tucson, AZ based on the 2011 5-year American Community Survey produced by the US Census Bureau. To interpolate median income values for each year prior to 2011, we obtained the median income growth rate for the state of Arizona over the sample period from the US Census Bureau. The real growth rate was applied to the 2011 real median income value for each census tract to estimate a unique value for each census tract, each year. The growth rate for the entire state of Arizona was used because yearly data was not available on a smaller, relevant spatial scale.

In addition to using the estimated yearly income value for each census tract, we used the annual assessed value of the each home to estimate income variation within each tract. To do this, the average assessed value for each tract was calculated for comparison to each home within each tract. Each home within each tract was assigned a home value index that was calculated as

$$Value\ Index_{iy} = \frac{Actual\ Assessed\ Value_{iy}}{Average\ Assessed\ Value_{cy}} \quad (3)$$

where:

C = census tract (there were 188 census tracts in the sample as designated by 2010 Census)
 i=1,2,...n
 y=2007,2008,2009,2010,2011

The calculated value index, which varies by year and by household, was then used as an index for scaling the calculated income value for each home within the census tract. The calculation of the final income variable was done using the formula in Equation 4 below.

$$\text{Real Household Income}_{iy} = \text{Real Median Income}_{cy} \times \text{Value Index}_{iy} \quad (4)$$

where:

C = census tract (there were 188 census tracts in the sample as designated by 2010 Census)
 i=1,2,...n
 y=2007,2008,2009,2010,2011

The resulting income estimates account for the heterogeneity of household income within each census tract. The calculation in (4) assigns a unique real income value to each household in the sample for each year in the sample period. Figure 6 shows the average income for each block segment by year. The annual income variable was divided by the number of months in a given year in the sample period to obtain a monthly income value.

[Figure 6]

Home Characteristics

In addition to accounting for the heterogeneity in household income, it is also important to account for the variation in the characteristics of each home that may influence water consumption. Individual home characteristics were obtained from the Pima County Assessor's Database on housing characteristics. The Assessor's database is updated yearly and contains detailed information on different attributes of a home. Table 5 below shows the list of housing attributes that were included in this empirical analysis.

[TABLE 5]

In addition to the different housing attributes listed in Table 5 above, several attributes were taken from the Assessor's database to estimate a value for potential landscapable area at each home. Landscapable area of a home is an important factor for water use in arid regions like the desert southwest, because most vegetation planted will require irrigation to survive. Equation 5 shows the calculation made to estimate potential landscapable area:

$$\text{Landscapable Area}_{iy} = L_{iy} - \frac{A_{iy}}{S_{iy}} - (G_{iy} \times 200) - P_{iy} \text{ sq. ft.} \quad (5)$$

where:

$$i = 1, \dots, n$$

$$y = 2007, \dots, 2011$$

L_{iy} =The area of the lot a home is built on in square feet

A_{iy} =The livable square footage of the home

S_{iy} =The number of stories of the home

$(G_{iy} \times 200)$ =The number of parking spaces in the garage or car port of a home multiplied by the 200, which is an estimate of the minimum square footage required to park an average car

P_{iy} =Approximate pool surface area

Weather Characteristics

Weather data was collected from two primary sources: The Arizona Meteorological Network's daily weather database and Pima County Flood Control's (PCFC) precipitation gauge database. Values for daily maximum temperature and maximum wind speed were collected from the AZMET database, while daily precipitation measures were obtained from the Pima County Flood Control rain gauge network. The PCFC network of 21 gauges was chosen over the single AZMET precipitation measuring station because rainfall events tend to be spatially heterogeneous throughout the city; this is especially true for summer monsoon rains.

The data for daily precipitation measures from 21 of PCFC's rain gauges located throughout the city were collected from PCFC's website. In addition to the precipitation measures, the latitude and longitude for the location of each of the 21 rain gauges was recorded. In order ensure that the precipitation measure used to explain variations in individual household water consumption was the most accurate, each household in the sample is assigned to the precipitation gauge that is nearest to the home.

In addition to assigning specific precipitation gauges to each household, we account for the variation in the billing cycle length and start date for each individual observation in the sample. Once completed, the maximum daily wind speed, maximum daily temperature and total daily precipitation measures were all averaged and assigned to the exact dates of each observation's billing period.

After accounting for billing cycle length, the precipitation and temperature variables were each separated into three seasonal weather variables. The seasonal separation was completed to account for the seasonality in the usage data, in addition to examining how weather events impact water use differently throughout the year. The seasonal separation is shown in Table 6.

[Table 6]

In this region, the seasonal separation for summer and winter is important because summer weather has a bigger impact on daily water use due to outdoor water use and evaporative cooling. Summer precipitation in Tucson also tends to be very different from the precipitation seen during the winter months. Tucson experiences summer monsoon rains,

which can come and go quickly at a specific location. Winter precipitation tends to be longer, and more spatially homogeneous. The “other seasons” variable was created because spring and fall months are fairly moderate weather months, which have very similar weather events.

Table 7 shows the mean value for each of the variables included in the demand models, separated by segment. The observed sample means for each of the household specific variables, such as income, pool area and landscapable area indicate that the segments constructed using univariate probability principles are different from one another in terms of observables.

[Table 7]

V. Residential Water Demand Estimation

After instrumenting average price per CCF for all households in each period, the demand for each of the four block segments was estimated using a random effects panel model. A random effects model was used for demand estimation because it allows for out-of-sample prediction. If a fixed effects model were used to estimate demand, it would not be appropriate to produce predicted values for future consumption behavior or for price responses outside the range of observed prices. Random effects models are also expected to have smaller standard error estimates than fixed effects models, as well as unbiased parameter estimates as long as there are no omitted variables that are heavily correlated with the explanatory variables (Wooldridge, 2010).

Equation 6 shows the demand model for SFR water users in Tucson Water’s service area. The model was estimated four times, one for each of the four user segments.

$$\begin{aligned}
LN(Usage_{it}) = & \beta_0 - \beta_1(Average\ Price\ IV)_{it} + \beta_2 \ln(Monthly\ Income)_{iy} + \beta_3(\#\ of\ Rooms)_{iy} + \\
& \beta_4(Evap.\ Cooler)_{iy} + \beta_5(Pool\ Area)_{iy} - \beta_6(Condition)_{iy} + \beta_7 \ln(Landscape\ Sq\ Ft.)_i + \\
& \beta_8(wind)_i - \beta_9 \ln(Summer\ Precip)_{it} - \beta_{10}(Winter\ Precip)_{it} - \\
& \beta_{11}(Fall\&\ Spring\ Precip)_{it} + \beta_{12}(Summer\ Temp)_{it} + \beta_{13}(Winter\ Temp)_{it} + \\
& \beta_{14} \ln(Fall\&\ Spring\ Temp)_{it} - \beta_{15}(Summer\ Precip \times Evap\ Cooler) - \\
& \beta_{16}(Summer\ Precip \times Pool\ Area) + \\
& \beta_{17}(Summer\ Temp \times Evap\ Cooler) \beta_{18}(Summer\ Temp \times Evap\ Cooler) + u_i + \varepsilon_{it} \quad (6)
\end{aligned}$$

Where:

$i=1,2,\dots,n$

$t=1,2,\dots,46$

$y=2007, \dots, 2011$

Using the explanatory variables outlined in (6), the random effects panel model for each user segment is estimated using a Feasible Generalized Least Squares (FGLS) procedure.

The expected sign of the explanatory relationship between each of the independent variables and household water consumption is shown in Table 8 in the column titled “Exp. Sign”. The level of significance, as calculated using robust standard error estimates, of each explanatory variable is indicated by the number asterisks indicating ***=1%, **=5% and *=10%. The overall level of significance of each segment’s demand model estimate is indicated by the value of the Wald test statistic. The Wald statistic for overall significance indicates that there is enough statistical evidence to show that all four of the models are significant in explaining the variation in SFR water use.

[Table 8]

Figure 7 shows the four demand curves for the respective user segments, estimated for the average summer use during the sample period July 2007-June 2011. The curves were estimated using the parameter estimates from Table 8 and the average value of each of the variables during the summer months of the sample period. Summer values were input since

summer months are the peak of water use in Tucson. As expected, the estimated demand curves for each of the four block segments shift outward from the origin as the usage requirement for placement within the segment increases—Segment 4 has the highest demand followed by Segment 3, Segment 2 and the segment for Block 1 having the lowest level of demand.

[Figure 7]

Price and Income effects

The estimated demand curves in Figure 7 shows the relationship between average price per unit consumed and quantity of water demanded. As expected, the average price of water has a significant estimated impact on water consumption, which is negative. Using the price coefficient estimates for each user segment, the price elasticity of demand, ϵ_p , can be estimated for each segment. Equation 7 shows the formula for price elasticity estimation.

$$\hat{\epsilon}_p = \frac{\partial q}{\partial p} \times \frac{p_{it}}{q_{it}} = \hat{\beta}_{average\ price} \times \frac{P_{it}}{\ln(Use)_{it}} \quad (7)$$

Table 9 shows the average price elasticity for each block segment for summer 2010 and the corresponding 95% confidence interval estimate. The confidence interval about the elasticity estimates are calculated using the sample distribution of the price variable. Though the elasticity estimate is close to zero, the confidence intervals for each segment does not include zero, so we can conclude with 95% confidence that the price response of users within each block is not equal to zero.

[Table 9]

Figure 8 shows the average price elasticity of demand for summer 2010 as a function of average price, with corresponding 95% confidence intervals. The elasticity estimates for blocks 3 and 4 show that users in segments 3 and 4 have price responses smaller (in absolute value) than blocks 1 and 2. Additionally, segments 3 and 4 are both statistically different from each other and from segments 1 and 2. The confidence interval for segment 1 has the largest range and becomes especially wide as average price increases. Though users consuming in block 1 see the lowest marginal price of all four blocks, due to the impact of surcharges, the average price seen by users who consume less than 15 CCF per month would appear to decrease as consumption increases, sending a price signal more similar to a decreasing block rate pricing scheme (see Figure 5b). The wide confidence bands about the segment one elasticity curve is probably due to the combined effects of decreasing per unit average price with the small variation in consumption observed in users in segment 1.

The small absolute value of ϵ_p shows that SFR water users in the Tucson Water service area are relatively unresponsive to price when making consumption decisions, though the significance of the statistic shows that that users do take price into consideration when making consumption decisions.

[Figure 8]

The calculated income variable is highly statistically significant in explaining household water demand. The positive effect of income on consumption is consistent with expectations and the estimated coefficient on the income variable is significant in explaining variations in water demand. To explore the income effect on water consumption for each user group, the

income elasticity of demand, ε_I , can be calculated using the income coefficient estimate from demand estimation and the formula shown in equation 8. The income elasticity estimates with 95% confidence interval are shown in Table 10.

$$\hat{\varepsilon}_I = \frac{\partial q}{\partial I} \times \frac{I_{it}}{q_{it}} = \hat{\beta}_{\ln(\text{monthly income})} \times \frac{\ln(\text{monthly income})}{\ln(Use)} \quad (8)$$

[Table 10]

Figure 9 (a) shows the segment-average income elasticity estimates over-time. Segments 1, 2, and 3 have 95% confidence intervals that overlap and thus we cannot conclude that income elasticities between the three segments are statistically different from each other. Segment 4, however, has a significantly larger income elasticity estimate than the three lower user segments. Panels (b), (c), and (d) of Figure 9 show that segment four's income elasticity estimates over the sample period are statistically different from each of the three lower user segments. This is likely due to the higher portion of income spent on water each month by segment 4 users as shown by the Bill to Income Ratio in Table 10. Though all four segments display relatively income-inelastic demand for water, there is a significant income effect on water consumption decisions.

[Figure 9]

The foregoing price elasticity results are consistent with those found in several recent studies of water demand in Phoenix, Arizona. Using cross-sectional quantile regressions at the census tract level for differences in consumption between 2000 and 2008, Yoo et al. find a price response that is higher and statistically significant at lower use quantiles as compared to high use quantiles. The magnitudes of the estimated price elasticities are much larger than those

here likely owing to the census tract-level data used and the longer period of comparison from 2000 to 2008. Klaiber et al., using census block group data and order statistics find a similar pattern of decreasing price response as the quantile of water use increases whether comparing a normal rainfall years (2000 to 2003) or normal to dry years (2000 to 2002). The same pattern of high users being less responsive to price is borne out whether in the summer or the winter.

VI. Conclusions

This article develops a detailed econometric model with a non-constant marginal price that shows how volumetric pricing affects water use at different levels and controls for the effects of different exogenous variables. The segmentation of water users by total consumption thresholds creates demand estimates for representative users corresponding to the price blocks of a given increasing block rate structure. Segmenting users for analysis using the barriers imposed by institutional constructs rather than order statistics allows for a more precise evaluation of the type of users choosing to consume within each block as well as the variation in response to exogenous shocks between user segments. The segmentation process outlined in this paper can be modified to incorporate different block thresholds imposed by different utilities. Additionally, due to the seasonal nature of water use in arid regions, an interested researcher can modify probability distributions to include only sample consumption during different seasons or time periods of interest.

The detailed panel of single-family residential water customers used for this analysis represents one of the most information rich datasets available in the literature. The detailed nature of the dataset allowed for the segmentation of users and the inclusion of variables

which work to capture the heterogeneity between users as well as changes in user behavior over time. The income specification in this project reflects an advance in incorporating a more precise household income in the water demand literature. The income effect is significant and positive and the median income of each segment increases as the block corresponding to each segment increases. Additionally, the largest users of water are most responsive to changes in income; this is mostly likely due to the aggressive four-tiered pricing structure used by Tucson Water.

The results from demand estimation suggest that the segmentation process is both necessary and effective at examining user responses. The range of variation in average monthly use between segments, shown in Figure 3, indicates that users in the four segments utilize water in different ways. The stacking of the segment demand shown in Figure 6 shows that user in different segments respond to price changes in different ways. Information gained from the different price responses for each user segment can be used to set block prices for water in a precise way with respect to a utility's conservation and revenue goals (Klawitter, Colby, & Thompson, 2014).

The low price elasticity estimates for the four user segments, shown in Table 3, are on the low end (in absolute value) of the estimates found in the water demand literature. The relatively low price responsiveness from users is most likely attributed to: 1) the low cost of water relative to income of users; 2) the complexity of the increasing block rate structure that makes it difficult for users to understand their marginal price when making consumption

decisions; and 3) the variable length of the billing cycle that makes it difficult for consumers to know how close they are to moving into a higher water use block within a billing structure.

As water resources become more stressed due to increased population and climate change, it will only become more important for water utility managers to have a more precise understanding of impacts that prices and exogenous variables have on their customers. Segmenting users into groups corresponding to institutional structures such as increasing block rate structures allows for managers to evaluate how pricing structure effect users within their service areas. Precise demand estimation allows for the best understanding of exogenous factors influencing water consumption.

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Tables

TABLE 1: Probability of Consuming in the Kth Block

Probabilities of consuming in each of Tucson Water's 4 Blocks		
Let: U = Probability of Consuming in a given block during the 48 month sample period		U ~GAMMA($\theta=0, \alpha=1.03, \beta=11.1$)
Block 4	$P(\mathbf{U} \geq 45 \text{ CCF})$	=0.019
Block 3	$P(30 \text{ CCF} \leq \mathbf{U} < 45 \text{ CCF})$	=0.04
Block 2	$P(15 \text{ CCF} \leq \mathbf{U} < 30 \text{ CCF})$	=0.21
Block 1	$P(0 \text{ CCF} < \mathbf{U} \leq 15 \text{ CCF})$	=0.73

TABLE 2: Segmentation Probability

Let: X = # of times a household consumes in block k, where k=1,2,3,4		X ~Binomial(48, $P=p(u_L \leq \mathbf{U} < u_U)$) Where: u_L =lower bound of block k and u_U =upper bound of block k
Block 4	$P(\mathbf{x} \geq 4 \text{ billing periods})$	=.013
Block 3	$P(\mathbf{x} \geq 6 \text{ billing periods})$	=.012
Block 2	$P(\mathbf{x} \geq 17 \text{ billing periods})$	=.015
Block 1	$P(\mathbf{x} \geq 45 \text{ billing periods})$	=.013

TABLE 3: Number of Households by Segment

Number of households by usage segment		
Block Segment	Number of households in Population	Number of Household in Sample
Segment 1	85,620	4,144
Segment 2	21,136	3,817
Segment 3	7,116	2,988
Segment 4	5,078	2,358

Table 4: Results for random effects model to estimate instrumental average price

Instrumental Variables by Block Segment				
	Block 1	Block 2	Block 3	Block 4
	# households=4,144	# households=3,817	# households=2,988	# households=2,358
	<i>Wald</i> =43,899.09	<i>Wald</i> =36,510.61	<i>Wald</i> =35,546.77	<i>Wald</i> =65,968.42
Variables	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$	$\hat{\beta}$
<i>Intercept</i>	-7.6***	-75.9***	-232.4***	-652.9***
<i>iv_1</i>	0.1***	0.1***	0.1***	0.1***
<i>iv_2</i>	-1467.7***	-2957.8***	-5422.9***	-12872.4***
<i>iv_3</i>	3205.8***	5423.0***	8707.7***	23064.0***
<i>iv_4</i>	-1547.9***	-2423.9***	-3622.0***	-10260.7***
<i>iv_5</i>	-3256.8***	-4837.6***	-6797.0***	-19845.0***
<i>iv_6</i>	1430.4***	2162.2***	3111.6***	9079.4***
<i>Sewer_serv</i>	-2.9***	-6.9***	-13.4***	-33.4***
<i>Level of Significance with Heteroskedastic Robust Standard Errors: *=10% **=5% ***=1%</i>				

TABLE 5: Assessor Housing Attributes

Housing Attribute	Description
Number of rooms	The total number of rooms in a home including all living spaces, not just bedrooms
Condition	A measure 1 through 4 that is assigned to each home based on the condition of the housing structure. A value of 4 is the best condition.
Evaporative Cooler	An indicator equal to 1 for a home with an evaporative cooling unit as the primary means of cooling; 0 otherwise.
Pool Area	The approximate square footage of the surface area of the pool at each home; = 0 if no pool

Table 6: Seasonal Separation for weather variables

Seasonal Separation	Months
Summer Weather Variable	June, July, August, September
Winter Weather Variable	December, January, February, March
Other Seasons Variable	April, May, October, November

Table 7: Variable Means by Segment

Variable	Variable Means by Segment			
	Segment 1	Segment 2	Segment 3	Segment 4
Normalized Usage (CCF)	3.71	5.58	8.33	21.54
Average Price IV per CCF	\$2.86	\$2.87	\$4.00	\$5.85
Monthly Income	4,378.68	4845.53	5453.4	6208.3
Condition	2.37	2.45	2.55	2.75
# of Rooms	10.55	8.72	8.51	8.87
Evap. Cooler	0.46	0.44	0.34	0.19
Pool Area (ft ²)	93.73	174.91	253	350.24
Landscapable Area	10,883.47	18,150.08	29,702.15	49,204.51
Wind	8.05	8.05	8.05	8.05
Summer Precip.	0.34	0.34	0.35	0.36
Winter Precip.	0.29	0.29	0.3	0.31
Fall/Spring Precip.	0.05	0.06	0.06	0.07
Summer Temp.	11.15	11.11	11.09	11.06
Winter Temp.	7.04	7.04	7.04	7.05
Fall/Spring Temp.	10.08	10.11	10.12	10.16
<i>Summer Precip. X Evap. Cooler=</i>	0.16	0.15	0.12	0.07
<i>Summer Precip. X Pool Area=</i>	0.34	0.62	0.9	1.27
<i>Summer Temp. X Evap. Cooler=</i>	5.17	4.89	3.77	2.1
<i>Summer Temp. X Pool Area=</i>	10.57	19.42	27.97	38.65

Table 8: Random Effects Estimation of Demand

Demand Estimation by Block Segment					
Dependent Variable = $\ln(\text{normalized monthly usage})_{it}$		Block 1	Block 2	Block 3	Block 4
		# households =4,144	# households =3,817	# households =2,988	# households =2,358
		Wald =6,813	Wald =27,406	Wald =29,093	Wald =15,933
Independent Variables	Exp. Sign	Coefficient Est.	Coefficient Est.	Coefficient Est.	Coefficient Est.
<i>Intercept</i>		0.3767	1.3217	1.2078	-0.1664
<i>Average Price</i>	(-)	-0.0804**	-0.1111***	-0.0693***	-0.0317***
<i>ln(Monthly Income)</i>	(+)	0.1126*	0.1359***	0.1697***	0.2787***
<i># of Rooms in household</i>	(+)	-0.0015*	-0.0002	0.0006	-0.0001
<i>Evaporative Cooler</i>	(+)	-0.0453*	-0.0030	-0.0075	0.0298
<i>Condition</i>	(-)	-0.0363*	-0.0307*	-0.0182*	0.0560*
<i>Pool Area</i>	(+)	0.0065*	-0.0005	0.0008	0.0023
<i>ln(Landscape Sq Ft.)</i>	(+)	0.0521*	0.0087	-0.0073	0.0324*
<i>Average Daily Max Wind Speed</i>	(+)	0.0327***	0.0382***	0.0329***	0.0097*
<i>Summer Precipitation</i>	(-)	-0.0378***	-0.0368***	-0.0550***	-0.0478***
<i>Winter Precipitation</i>	(-)	-0.0076	0.0113*	0.0092*	-0.0203*
<i>Spring/Fall Precipitation</i>	(-)	-0.0790**	-0.0415**	-0.0663**	-0.1144***
<i>Average Summer Max. Temp.</i>	(+)	0.0066**	0.0096***	0.0181***	0.0255***
<i>Average Winter Max. Temp.</i>	(+)	0.0055**	0.0069***	0.0143***	0.0235***
<i>Average Spring/Fall Max Temp.</i>	(+)	0.0075**	0.0099***	0.0181***	0.0267***
<i>Summer Precip. X Evap. Cooler</i>	(-)	-0.0124*	-0.0159**	-0.0174*	-0.0155*
<i>Summer Precip. X Pool Area</i>	(-)	-0.0002	-0.0009*	0.0001	-0.0001
<i>Summer Temp. X Evap. Cooler</i>	(+)	0.003**	0.002**	0.002**	0.002**
<i>Summer Temp. X Pool Area</i>	(+)	0.0001	0.0001	-0.0001	0.0001
<i>Level of Significance with Heteroskedastic Robust Standard Errors: * =10% ** =5% *** =1%</i>					

Table 9: Average Summer Price Elasticity of Demand by User Segment

Block Segment	$\widehat{\epsilon}_{ap}$	95% Confidence Interval	
		$\widehat{\epsilon}_{ap LB}$	$\widehat{\epsilon}_{ap UB}$
Segment 1	-0.09	-0.03	-0.46
Segment 2	-0.12	-0.04	-0.31
Segment 3	-0.08	-0.03	-0.28
Segment 4	-0.04	-0.01	-0.18

Table 10: Average Income Elasticity of Demand by User Segment and Water Bill to Income Ratio

Block Segment	Bill to Income Ratio	$\hat{\epsilon}_I$	95% Confidence Interval	
			$\widehat{\epsilon}_{I LB}$	$\widehat{\epsilon}_{I UB}$
Segment 1	.4%	.41	0.35	0.55
Segment 2	1%	.39	0.36	0.45
Segment 3	1.6%	.43	0.41	0.52
Segment 4	3%	.64	0.59	0.78

List of Figures

Figure 1: Single Family Residential Water Use, Tucson Water Service Area 1985-2012

- A) Total SFR consumption with 12 month running average trend line
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Figure 2: Typical Econometric Models for Water Demand Estimation

Figure 3: Gamma Family Distribution for Monthly Water Consumption

Figure 4: Average Monthly Use by Segment

Figure 5: Increasing Block Rate Schedule and Average Price of Water

- A) Increasing Block Rate Schedule by Year (2011 Dollars)
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Figure 7: Estimated Household Demand by User Segment

Figure 8: Price Elasticity of Demand by User Segment

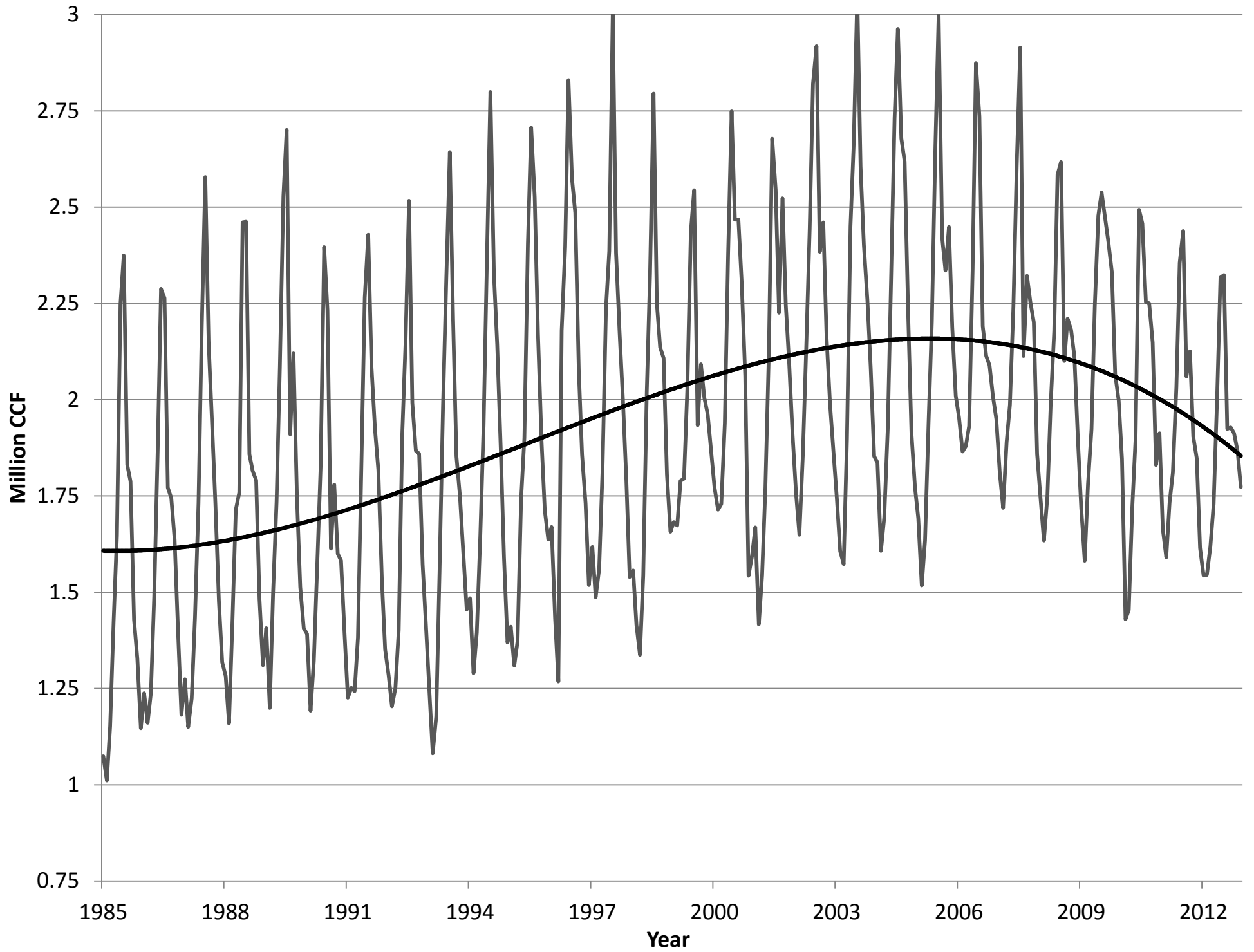
Figure 9: Income Elasticity of Demand by User Segment

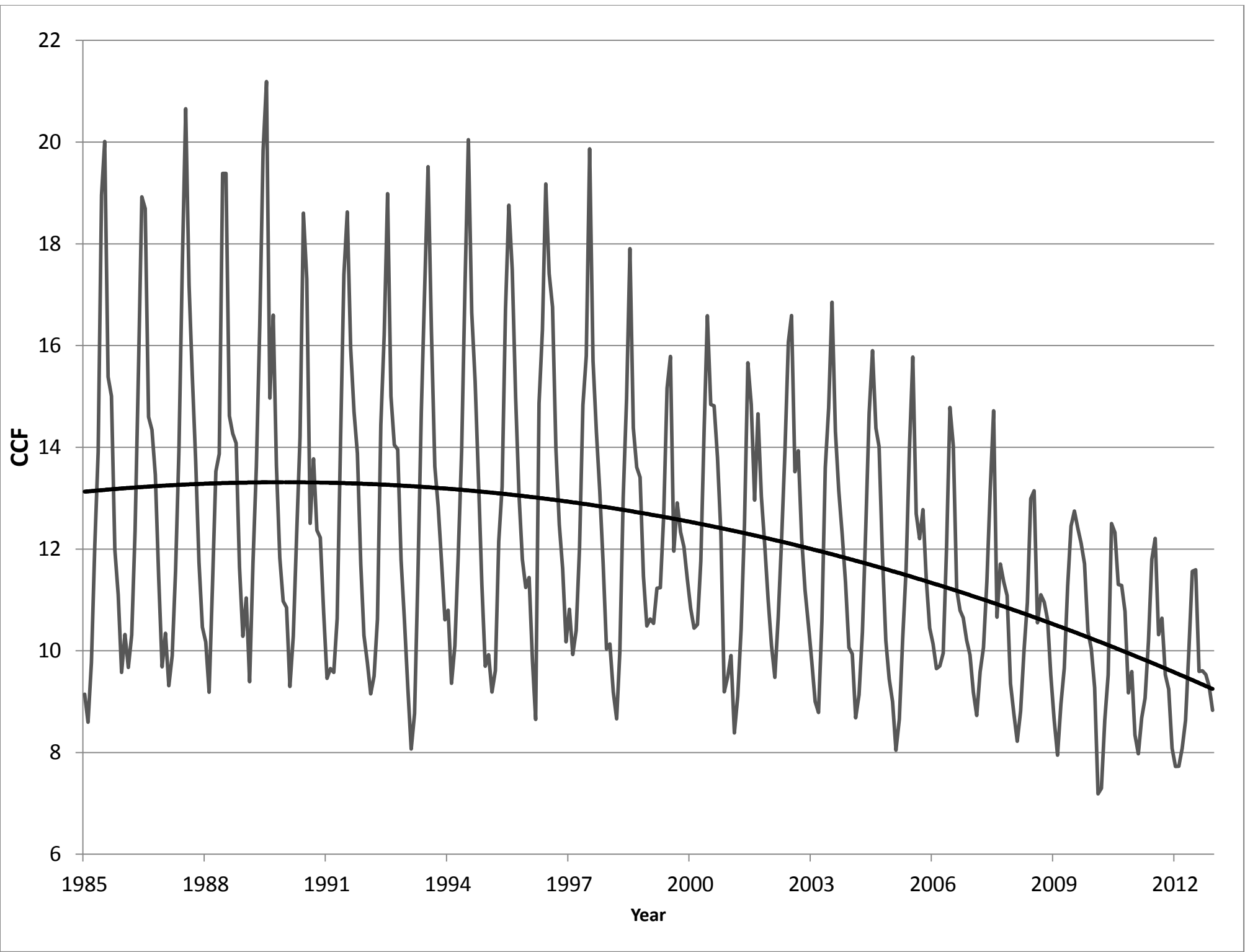
Footnotes

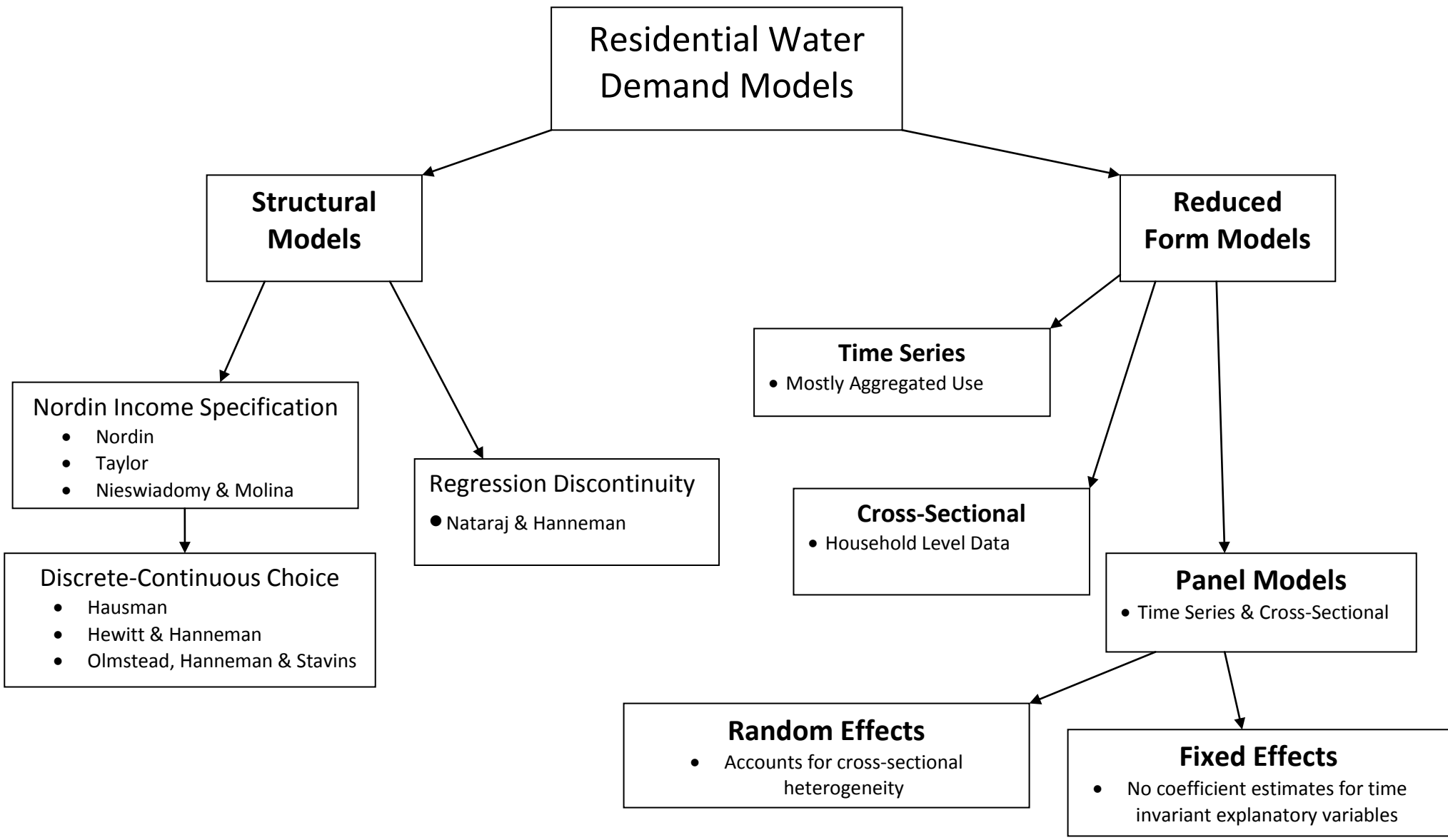
- 1) Although an unbalanced panel could have been used, we would need to model explicitly the non-random mechanism in the data generating process leading to the construction of new houses and their addition over time to the panel. Developing such a model is beyond the focus of the current analysis.
- 2) Using the results from the Binomial calculations in table 2, placing the users into their segments was performed using a hierarchal structure. The process was performed as follows: if a user consumed in block 4 at least four times during the 48 month sample period, they were placed in the segment for block 4 (Segment 4). If the consumer did not meet the criteria to be placed in block 4, the consumer would then be considered for block 3's segment (Segment 3). If the user consumed in block 3 at least six times during the 48 month period, they would be placed in block 3. If the consumer did not meet the criteria to be placed in Segment 3, the consumer would then be considered for block 2's segment (Segment 2). If the customer consumed in block 2 at least 17 times during the 48 month period, they would be placed in Segment 2. Since we were interested in all of the variation in usage, all users who did not meet the criteria for any of the upper three usage segments were defaulted to be designated as block 1 user's (Segment 1).
- 3) A Durbin-Wu-Hausman test Davidson, R., & McKinnon, J. G. (1993). *estimation and inference in econometrics*. New York: Oxford University Press. was performed in which the residuals from the instrumental variables equations (2), \hat{v}_{it} , were inserted into the random-effects model as follows

$$y_{it} = \mathbf{x}'_{it}\boldsymbol{\beta} + \gamma\hat{v}_{it} + u_i + \varepsilon_{it}$$

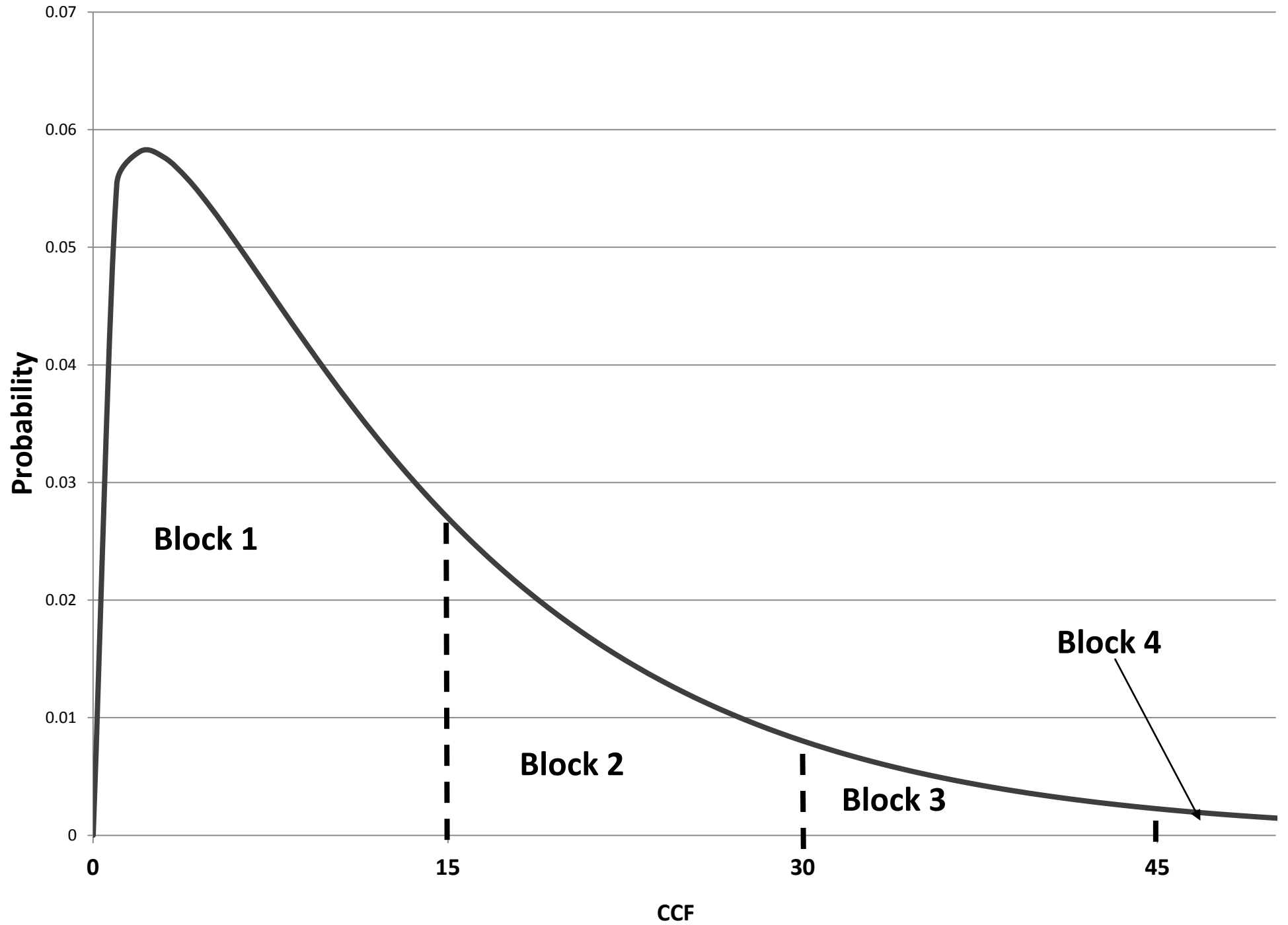
for each of the four segments. The observed χ^2 statistic values for segments 1 through 4 were 354.5, 187.6, 52.9, and 44.8, respectively, all with asymptotic probability $<.0001$. The null of no correlation between the residuals and the error terms is rejected in all cases, indicating an instrumented average price should be included to address simultaneity bias.

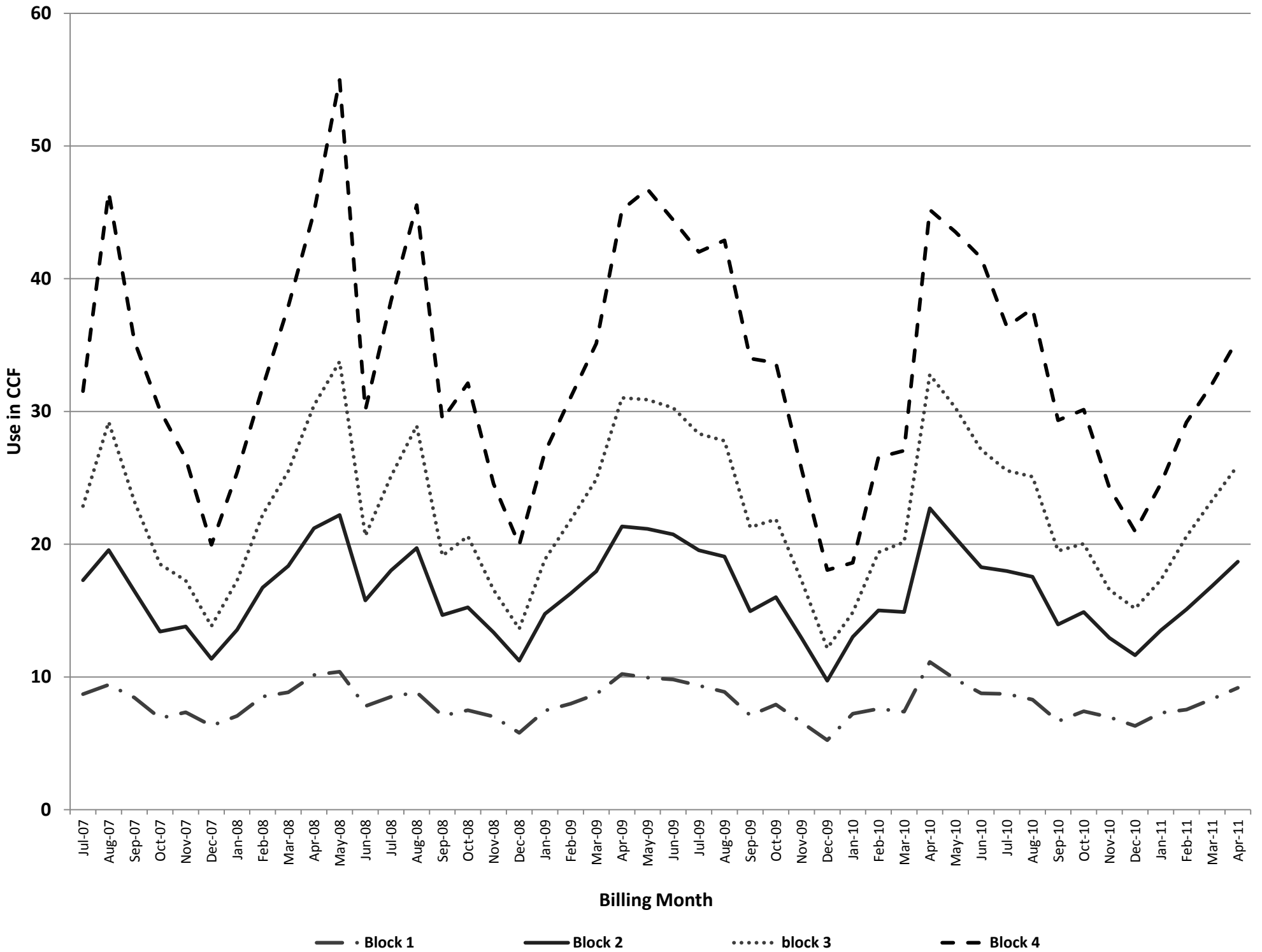


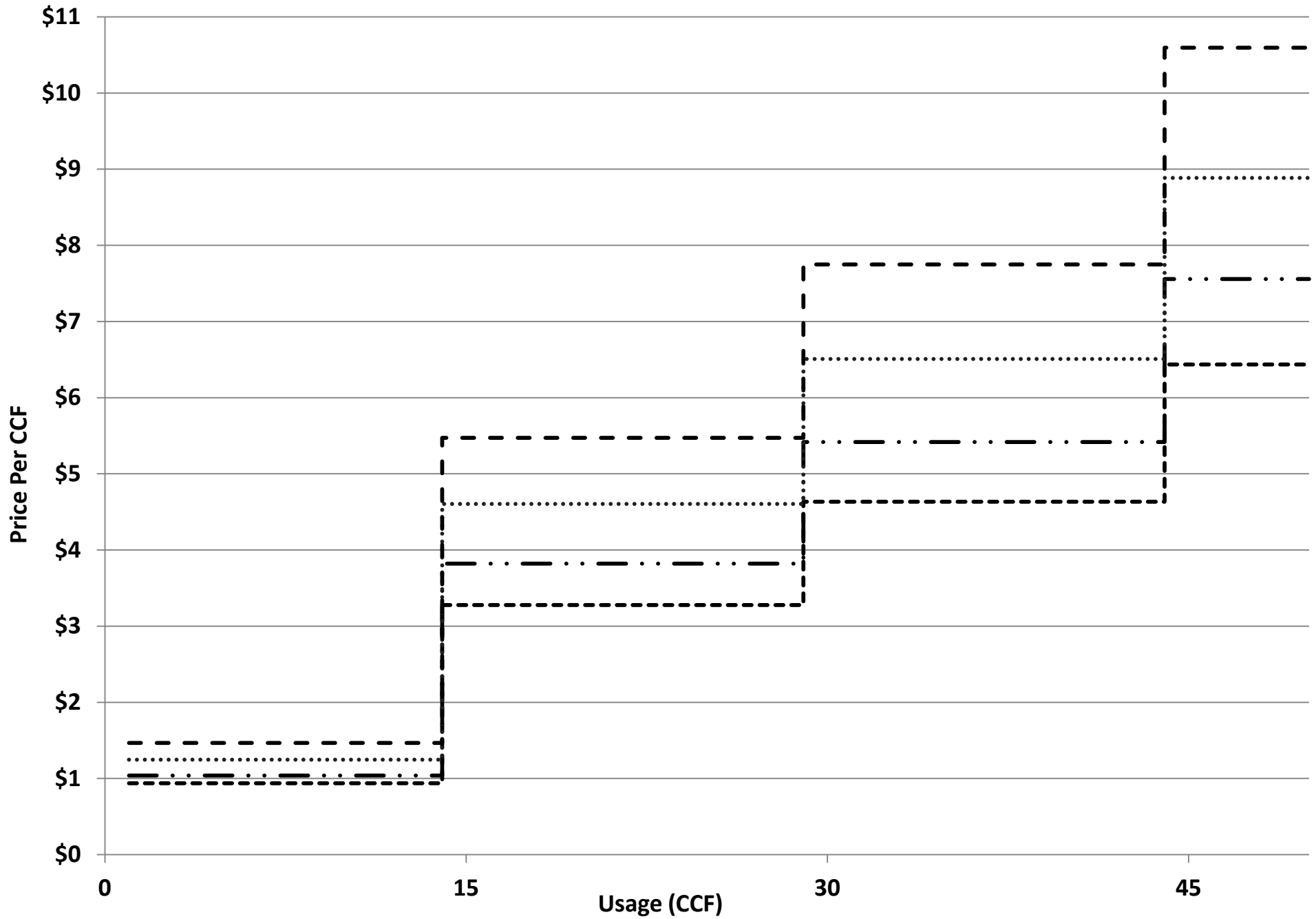




PDF Gamma Family Distribution ($\alpha=1.03, \beta=11.1$)





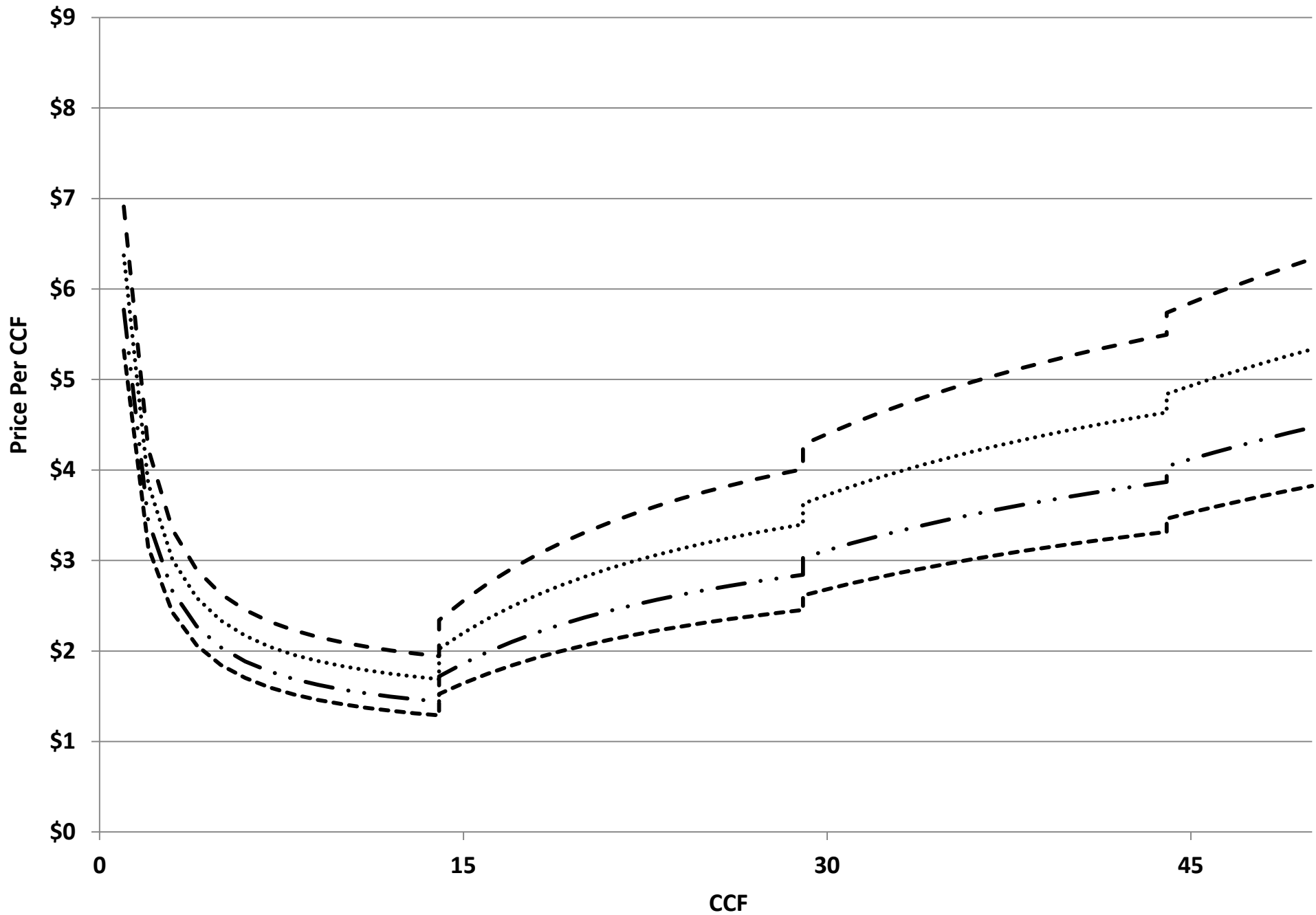


--- Jul 2007- Jun 2008

- · Jul 2008- Jun 2009

..... Jul 2009-Jun 2010

- - Jul 2010 - Jun 2011

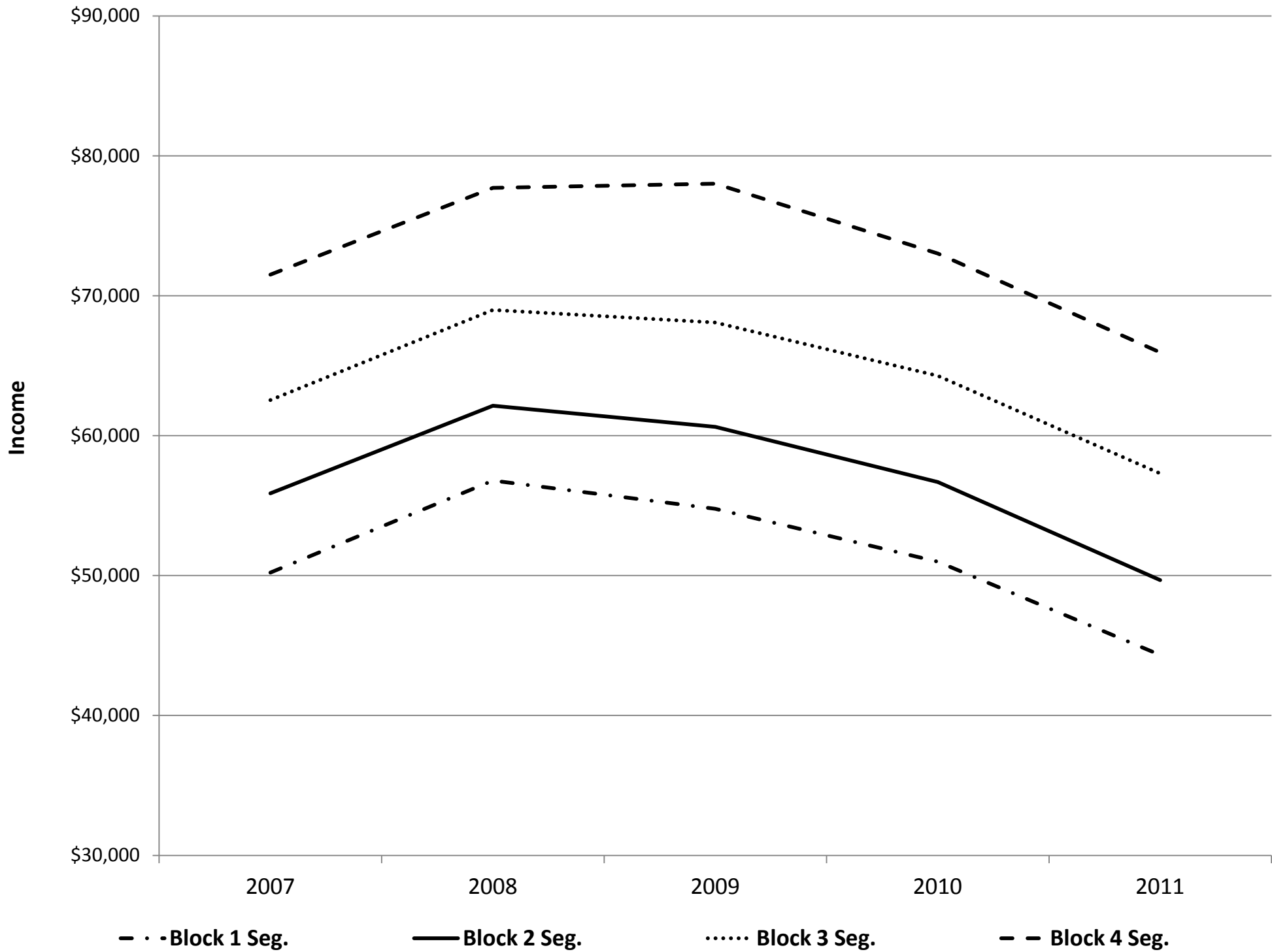


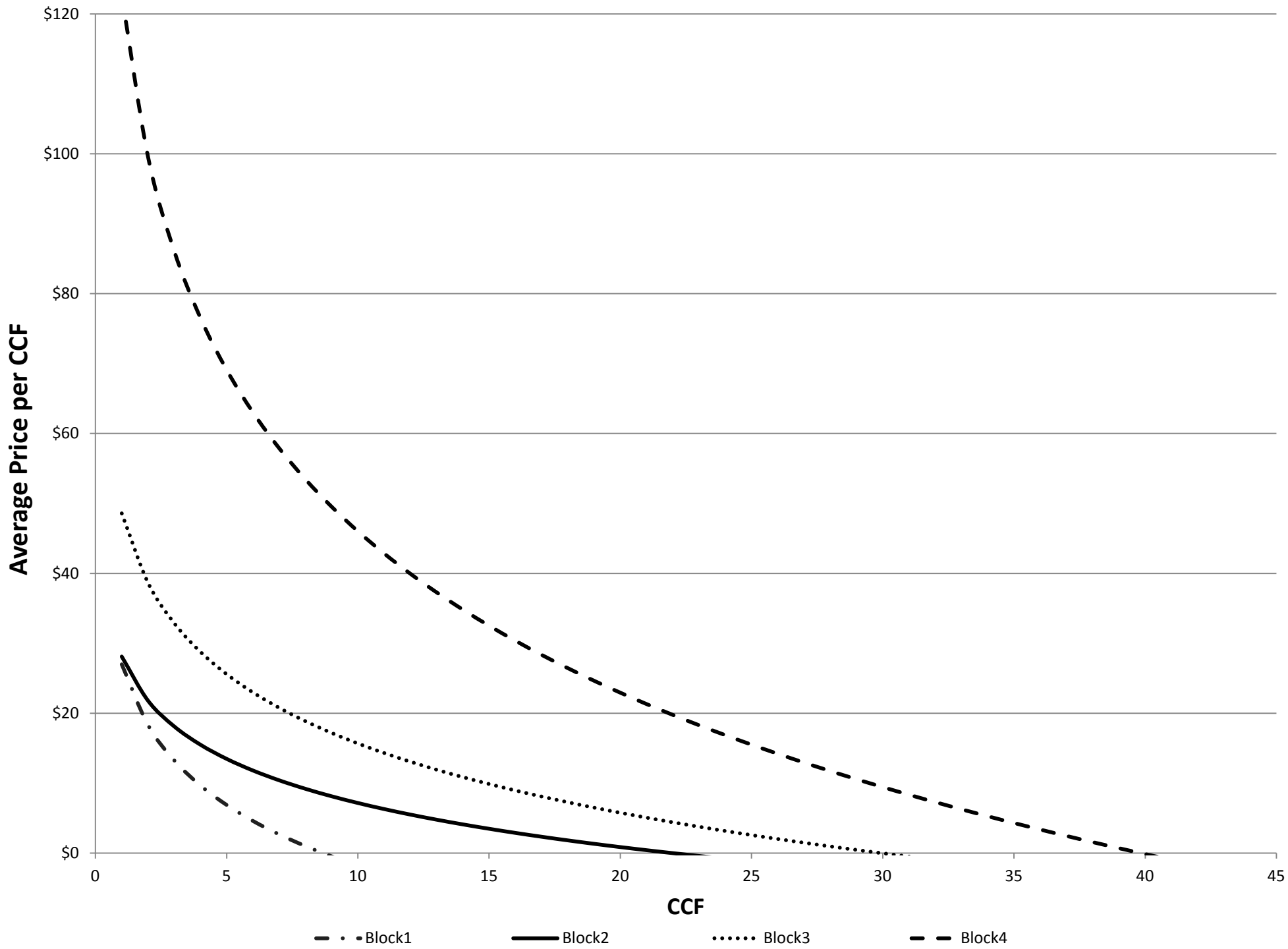
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— · AP 2008-2009

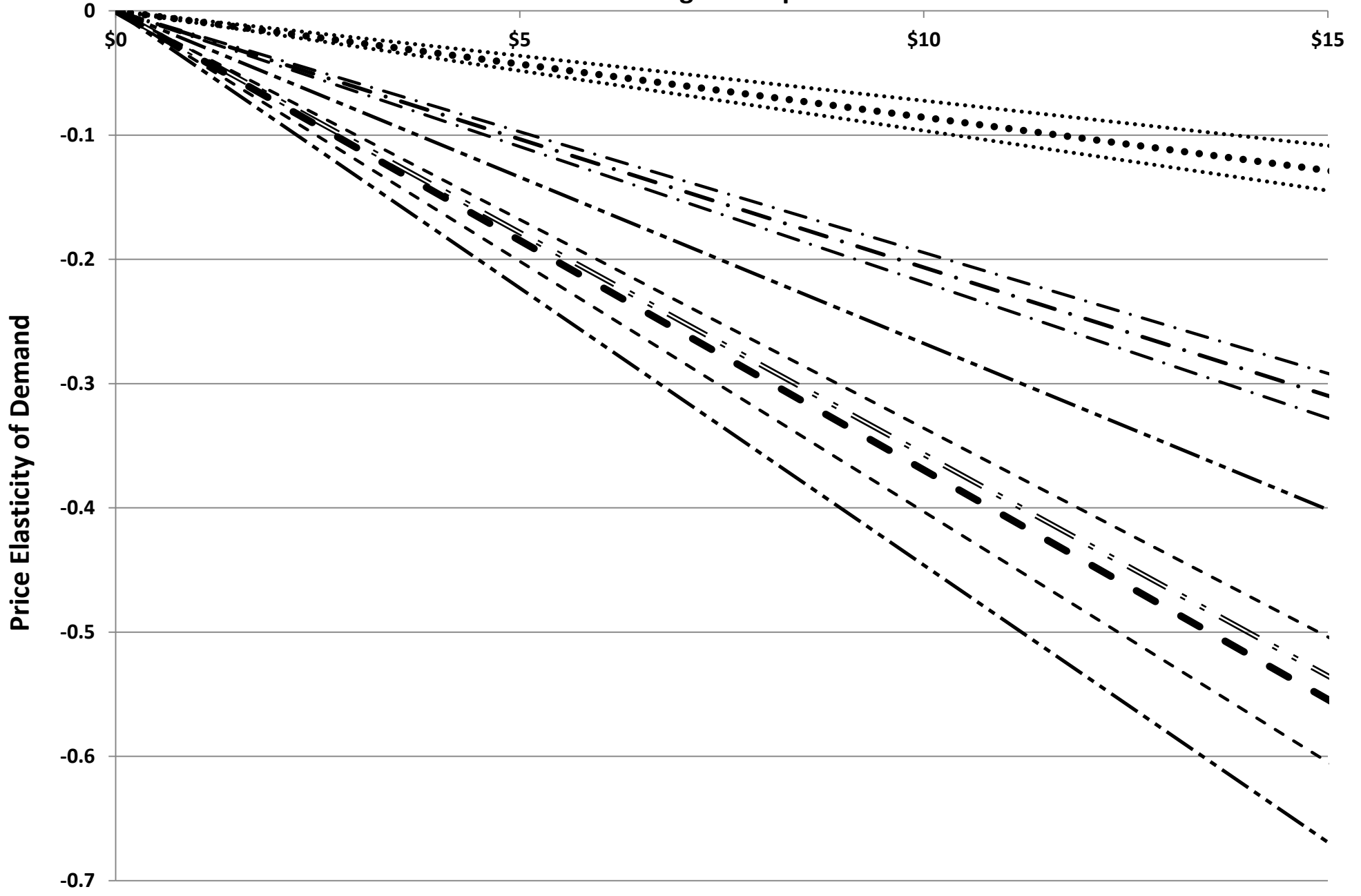
..... AP 2009-2010

- - AP 2010-2011





Average Price per CCF



==== Seg 1 Elasticity

— — Seg 1 95% Confidence

— Seg 2 Elasticity

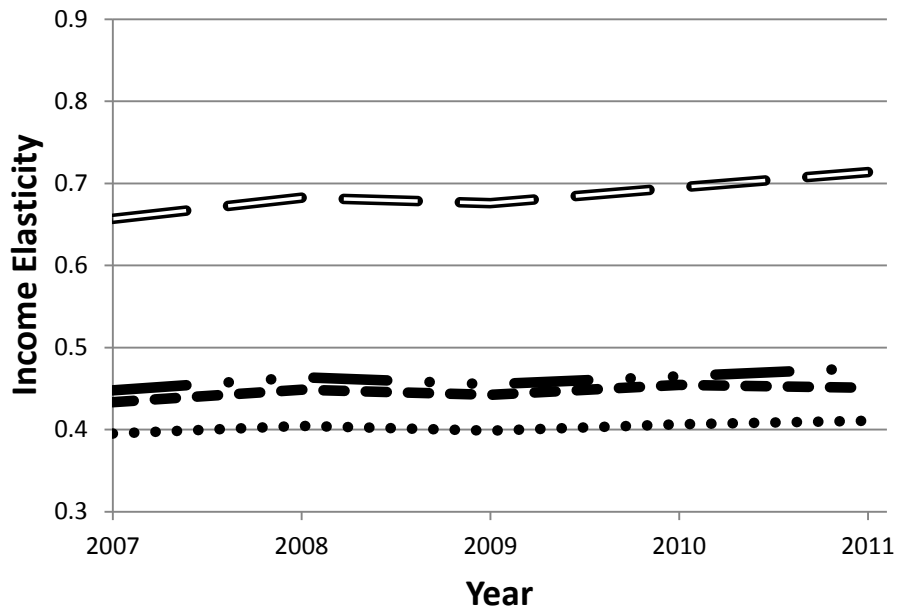
- - - Seg 2 95% Confidence

— • Seg 3 Elasticity

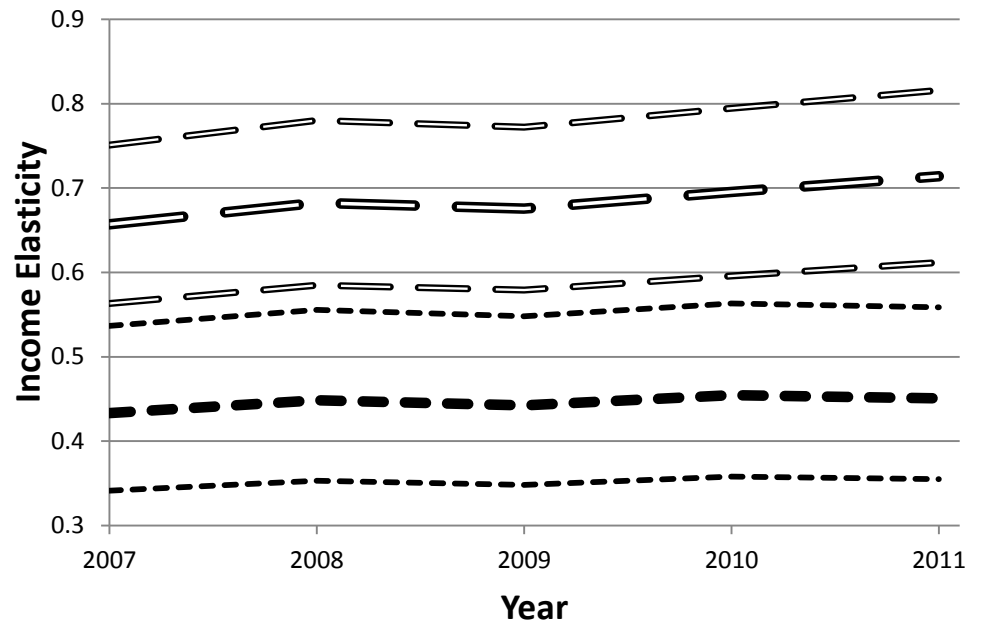
- • Seg 3 95% Confidence

• • • Seg 4 Elasticity

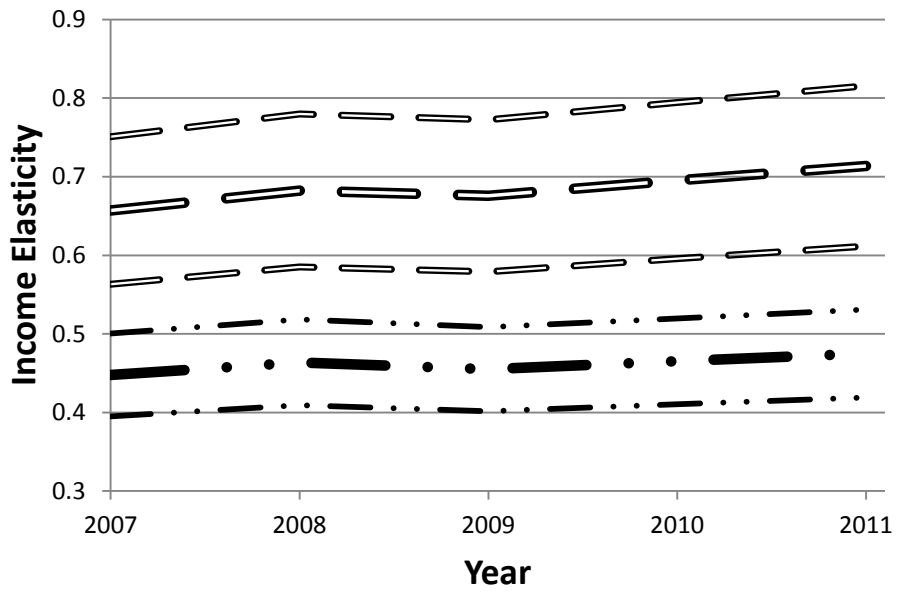
• • • • Seg 4 95% Confidence



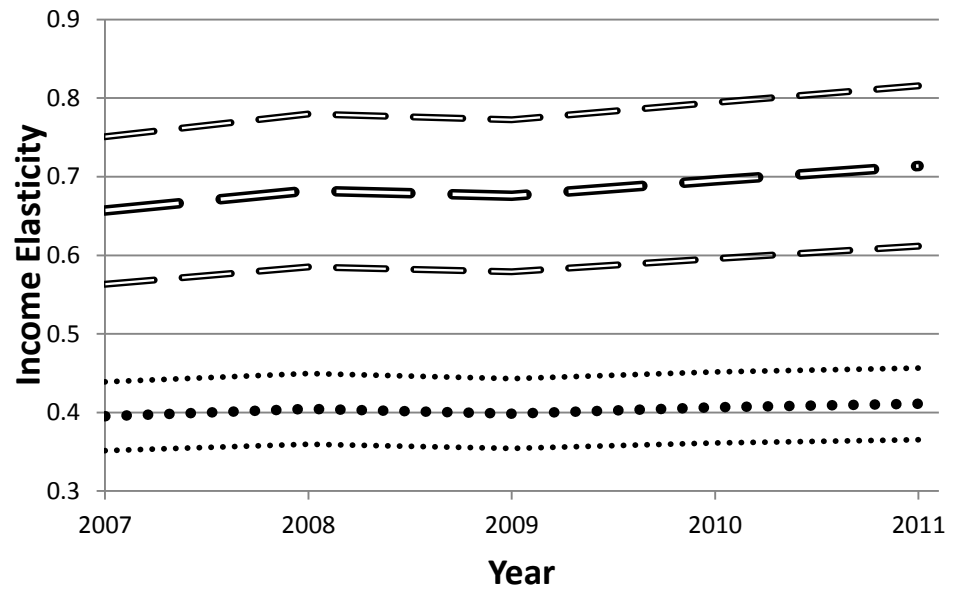
(a)



(b)



(c)



(d)

