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The Role of Mechanical Refrigeration in Spatial and Temporal Price Dynamics for Regional U.S. Egg Markets, 1880–1911

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Abstract

This paper examines the role of mechanical refrigeration in temporal and spatial price relationships for regional egg markets in the United States, 1880–1911. Notably, this period encompasses an era in which widespread adoption of mechanical refrigeration greatly impacted the ability to briefly store otherwise perishable items. This development in turn altered observed price dynamics for many perishable commodities, including fresh eggs. We use a class of time series models, time–varying autoregressions (TVARs), to document both the structural change and the corresponding impact on spatial price dynamics for U.S. regional egg price relationships during the late 19th and early 20th centuries.

Keywords: Egg prices; Half life; Law of one price; Refrigeration; Structural change; Time–varying smooth transition autoregression

JEL Classification Codes: C22; N91; R11; Q13

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1 Introduction

The wide–scale adoption of refrigeration in the storage and processing of agricultural commodities proceeded in two stages: The first phase, which began in the late 1870s, employed natural ice in the shipping of beef and pork (Aduddell and Cain, 1973, 1981; Anderson, 1953; Kujovich, 1970). The second phase, which began in the 1880s, employed mechanical refrigeration in the storage of a wide range of commodities, including, not only beef and pork, but also butter, cheese, and eggs. Even though the ancients understood the physics of refrigeration, the technological bottleneck limiting wide–spread use was in building a reliable, low–cost mechanical refrigerator. Indeed, doing so was only accomplished in the final two decades of the nineteenth century, and even these early mechanical refrigerators could not be profitably employed in the shipping of perishables. Size, maintenance, and the absence of a consistent power source forced shippers to use ice to refrigerate rail cars well into the twentieth century (see, e.g., Goodwin, Grennes and Craig, 2002).

Previous scholarly work on the economic impact of refrigeration has focused on three changes in the market for perishable commodities: (1) the spatial integration; (2) structural change; and (3) the welfare effects. With respect to spatial integration, Serra and Goodwin (2004) and Serra et al. (2006) estimate the impact on regional prices differences in the U.S. egg market and find that "price shocks in one market generate responses in the other markets, leading to a tendency for prices to converge after market shocks" (p. 70). Craig and Holt (2008)and Holt and Craig (2006) model structural changes in the hog–cycle cycle as a result of the introduction of the refrigeration in the shipping and storage of pork and conclude that, between 1870 and 1940, "the cycle underwent fundamental seasonal change, which was largely the result of mechanical refrigeration" (p. 49). And, with respect to the welfare effects of refrigeration, Craig et al. (2004) estimate that, in the United States, the adoption of refrigeration in the late–nineteenth–century "resulted in an increase of 1.26 percent of national income" (p. 332).

In this paper, we investigate the impact of refrigeration on the market for eggs, focusing on changes in both the spatial and temporal price dynamics. Previous studies have emphasized refrigeration's impact on the spatial dimension of market integration;

however, mechanical refrigeration employed in storage facilitated arbitrage over time as well as space, and there were important welfare effects from this opportunity. Interestingly, the effect on the market from the resulting temporal smoothing often conflicted with the impact from spatial integration. In short, refrigeration in shipping, and the absence of refrigeration in storage, forced farmers and wholesalers holding a perishable commodity to ship to another market as quickly as possible, usually a more–distant urban area, a phenomenon well–documented in the spatial integration literature. But once mechanical refrigeration was available for storage, sellers could hold their perishable inventories for sale in the local market or a closer urban area. This logic has implications for the impact on the price dynamics for perishables and the welfare effects of refrigeration.

2 Regional U.S. Egg Markets: An Historical Perspective

On the eve of the Civil War, U.S. farmers produced 633 million dozen eggs, with a market value of $51 million. By 1910, the market had grown to 2,250 million dozen, with a market value of $470 million.[1] During that 50 year period, per capita egg production increased at an average compounded rate of 2.6 percent per annum, which was substantially faster than the 2.2 percent growth experienced by the U.S. population, and, as a result, per capita annual egg consumption increased from 20.1 dozen to 24.6 dozen. At the same time, the urban share of the population grew at 3.6 percent annually, and the farm share of the labor force declined by 1.1 percent annually. Thus, U.S. farmers increased dramatically the productivity of their poultry operations. Indeed, the annual egg output per hen increased by a factor of 2.5, nearly two percent per annum.

These changes were facilitated by two important technological innovations: The expansion of the rail network, and transportation improvements more generally, and the wider use of refrigeration in both shipping and storage. Refrigeration had an especially strong, and often overlooked, impact on the markets for perishable agricultural commodities. Once farmers, processors, wholesalers, and retailers could refrigerate

[1] These are nominal figures; however, the price level in 1910 was roughly the same as it was in 1870 (Clark, Craig and Wilson, 2003, p. 226).

some critical proportion of the product, the possibilities for arbitrage over space and time expanded, with the result that markets became more integrated, by various measures of the term. It follows that price differentials between places and points in time fell, and, other changes aside, the prices in formally off-peak seasons decreased as quantities exchanged increased; while formally peak-season prices increased and quantities decreased, with resulting welfare and real output gains (Holt and Craig, 2006; Craig and Holt, 2008; Goodwin, Grennes and Craig, 2002; Craig, Goodwin and Grennes, 2004).

While in general refrigeration facilitated geographical market integration, and thus arbitrage over space and time, the effects of "natural" refrigeration–that is, through ice–and mechanical refrigeration were potentially quite different. The use of refrigerated rail cars antedated the widespread use of mechanical refrigeration. The first large-scale applications were in the shipping of slaughtered beef and hogs. The carcasses were hung in rail cars with slated sides, and in the four corners of the cars were bins in which fresh ice was packed. As the cars moved down the line the air blowing through the slats passed by the ice bins and circulated cooler air among the carcasses. Because the carcasses did not reach all the way from ceiling to floor, there was room at the bottom of the car for packing dairy products (mainly butter and cheese) and eggs. This system offered arbitrage opportunities primarily between locations, mainly the Midwest, where the products were processed and the urban areas to the east.

Refrigerated storage, which was primarily generated mechanical refrigerators, on the other hand, primarily facilitated the arbitrage over time, as processors and wholesalers could store inventories to meet future market demand.[2] It was possible that the two types of refrigeration sent conflicting signals to sellers.

For example, suppose a processor or wholesaler recognizes a price differential of delta between locations X (the source of the commodity) and Y (where the commodity is demanded), and suppose delta is greater than epsilon, which is the cost of refrigerated shipping. As a result of the trade between X and Y, the market price would increase in X and decrease in Y. Econometric tests might show a decrease in the half-life between the period before refrigerated shipping as available and after.

[2] Ice was not a good cooling agent for storage, because the endothermic process that generates lower temperatures also results in melting, and the moisture damaged perishables.

Now suppose that not only can processors or wholesalers ship via refrigerated rail cars, but they can also warehouse with mechanical refrigeration at either end of the rail line, again X and Y. Further suppose that at either end of the line, the price differential phi between time t and t+n, is greater than epsilon star, which is the cost of refrigerated storage. If phi less epsilon star is greater the delta less epsilon, then it paid to store and arbitrage over time in X rather than over space between X and Y. As a result, not all of the epsilon opportunities would be exploited. Indeed, there may have been opportunities to ship before mechanical refrigeration that are no longer profitable, and, importantly, the econometric manifestation of this would an increase in half-lives.

Now, the market can work this out over time by adjusting supply; however, the "over time" qualifier is important. The storage technology was improving fairly continuously throughout the period in question; so for a period of time, captured by our data range, the arbitrage opportunities in time might have expanded more rapidly than the physical supply responses to the increasing arbitrage opportunities in space.

To see this practice, consider two sets of cities, first, say, either Dubuque–Chicago or Indianapolis-Chicago. Our data reveal that, in both cases, Chicago was typically the higher-priced market, and was therefore in general a net importer of eggs from the hinterlands. It is approximately 178 miles from Dubuque to downtown Chicago. Likewise, it is about 183 miles from downtown Indianapolis to downtown Chicago, and both cities were connected by rail to Chicago. We find that the Dubuque–Chicago and the Indianapolis-Chicago egg markets were reasonably integrated, by econometric standards, both before and after the approximate period in which mechanical refrigeration became available on a commercial basis. Of interest, however, is the fact that the dynamics in these markets did not change in the slightest with the expansion of mechanical refrigeration. In Indianapolis, for example, the half-life of a shock to the price difference (between Chicago and Indianapolis) remained steady over the entire sample period at 0.77 months, or about three weeks. The comparable estimate for Chicago–Dubuque is 0.40 months, or about two weeks. We argue that these markets were fairly well integrated, via refrigerated rail car before the beginning of the period we consider here, and that a reasonable proportion of marketable surplus of eggs was being sent from both Indianapolis and Dubuque top Chicago both before and after the introduction of mechanical refrigeration. Nothing much changed, in other words.

It's not that refrigeration and temporal storage didn't become an option in either city; it's just likely that, at the margin, the cost of doing so did not in general exceed the expected profit of continuing to ship eggs to Chicago.

An alternative scenario is St. Louis, which is just shy of 300 miles from Chicago. Here, with the technical change being centered somewhere around 1899, the half life of a shock in the Chicago-St. Louis price relationship went from being 0.25 (about one week) to 2.00 (four weeks). We interpret this as saying that, at the margin, there was less shipping from St. Louis to Chicago after the technical change and more local "storage." Of course shipments to other locations could have changed, too. But we think this is a key finding. With the expansion of mechanical refrigeration and storage, the arbitrage profits over time locally dominated the arbitrage profits over space between St. Louis and Chicago. The technological change resulted in less trade.

3 Spatial Price Linkages: Conceptual and Empirical Issues

3.1 The Law of One Price: Some Simple Analytics

The data we analyze in subsequent sections are comprised of wholesale egg prices for a variety of U.S. cities during the late 19th and early 20th centuries. In this section we present a simple model of spatial price relationships for commodities priced in the same currency. In doing so we build on the basic framework presented by Lo and Zivot (2001) and O'Connell and Wei (2002), and others, although the modern underpinnings for the theory of spatial price relationships are typically attributed to Dumas (1992).

Let P_{it} and P_{jt} denote wholesale egg prices, in cents per dozen, at time t in cities i and j, respectively. The spatial relationship between these prices at time t may then be expressed as:

$$P_{it} \;=\; \tilde{\alpha} P_{jt}^{\beta} \exp\left(\varepsilon_t\right), \tag{1}$$

or, after taking natural logarithms,

$$p_{it} \;=\; \alpha + \beta p_{jt} + \varepsilon_t, \tag{2}$$

where $t = 1, \ldots, T$; $p_{\ell t} = \ln(P_{\ell t})$, $\ell = i, j$; $\alpha = \ln \tilde{\alpha}$, with $\tilde{\alpha}$ denoting the proportion of the price in city j attributable to shipping and transport costs (i.e., shipping costs are assumed to be of the "iceberg" variety); and ε_t is an idiosyncratic error term such that $\varepsilon_t \sim N(0, \sigma^2)\ \forall t,\ t = 1, \ldots, T$. A typical assumption in the Law of One Price (LOP) literature is that $\beta = 1$; see, for example, Goodwin et al. (2002). Under this assumption it is a straightforward matter to rearrange (2) as follows:

$$y_t \ = \ \ln(P_{it}/P_{jt}) = \alpha + \varepsilon_t. \tag{3}$$

Equation (3) simply states that, under the assumed conditions, the LOP holds if log price differentials equal a constant term plus a mean–zero idiosyncratic shock. At this point the time series properties of the data are typically invoked to aid in the interpretation of the LOP condition. Specifically, there is considerable evidence that most medium–frequency prices, even in logarithmic form, behave in a manner consistent with the unit root hypothesis; see (Balagtas and Holt, 2009) for a reasonably current review. That is, we could think of expressing the underlying statistical model for city prices as:

$$\Delta p_{\ell t} \ = \ \upsilon_t,\ \ell = i, j, \tag{4}$$

where Δ is a first difference operator such that $\Delta z_t = z_t - z_{t-1}$ and where $\upsilon_{\ell t} \sim \text{iid}\left(0, \sigma^2_{p_{\ell t}}\right)$. Of course it is always possible to add either a drift term (i.e., an intercept) or lagged values of $\Delta p_{\ell t}$ to (4) as required, although doing so will not alter the underlying model implications. Assuming that (4) is a reasonable description of movements in nominal prices, it follows that the relative price relationship in (3) can be interpreted as a cointegrating relationship, assuming, of course, that ε_t, although possibly autocorrelated, does not contain a unit root. In other words, expressing (3) is rewritten in first difference form, we obtain:

$$\Delta y_t \ = \ \delta_0 + \sum_{k=1}^{p} \phi_k \Delta y_{t-k} + \rho y_{t-1} + \varepsilon_t, \tag{5}$$

where an intercept term, δ, has been added (an assumption consistent with the presence of a deterministic linear trend in (3). As well, lagged values of Δy_t have also been added under the assumption that the errors of the relative price relationship are autocorrelated, in this case up to lag order $p + 1$.

The coefficient of primary interest in regression equation (5) is the parameter ρ, the coefficient on the lagged log price differential. specifically, ρ indicates the degree to which egg markets in city i and city j are integrated. Assuming the above arguments regarding the statistical behavior of these prices and the LOP are correct, then we would ordinarily expect to obtain an estimated value for ρ that is negative and that is less than one in absolute value. The closer the estimated (absolute) value of ρ is to zero, the less integrated are the markets in question, and the longer time required for the LOP equilibrium to be restored following a transitory price shock. Alternatively, the greater is the estimated (absolute) value of ρ, the more more highly integrated are the respective markets in question, and the more quickly will the LOP equilibrium be restored following a transitory shock.

In the law–of–one price literature it is common to express the rapidity with which market equilibrium is restored following a transitory sock by computing and reporting the so called half–life measure, defined as:

$$\hat{h} = \frac{\ln(0.5)}{\ln(1+\hat{\rho})}, \tag{6}$$

where $\hat{\rho}$ is the estimated value for ρ based on (5). The value of reporting half lives is that they are measured in time units (i.e., in the same time frequency as the data being analyzed), and therefore estimates can be readily compared for different market pairs and even for differing commodities. In any event, the half life measure in (6) indicates the amount of elapsed time required (again, where time is measured in the same frequency as that for the data being analyzed) for half of the effects of a transitory shock away from the LOP fundamental to dissipate.

3.2 Recent Developments: Transactions Costs

A common empirical finding in LOP studies is that estimates of ρ are larger than would otherwise be anticipated (correspondingly, estimates of ρ are much closer to zero in absolute terms than would be anticipated) based on institutional knowledge regarding trade amongst the markets in question.[3] The result is that economist have

[3] Similar results are frequently obtained as well in the related Purchasing Power Parity (PPP) literature.

sought to explore the LOP using alternative frameworks.

An approach that has gained popularity in recent years is to assume that otherwise unobserved transactions costs play an important role. See, for example, Goodwin and Piggott (2001) and Lo and Zivot (2001). The idea is that for real trade, transactions costs, defined by, for example, insurance, freight, legal fees, and so forth, matter. Small price deviations, that is, small movements of p_{it} away from p_{jt} will likely not generate any meaningful arbitrage activity because such movements may, in general, not be large enough to cover the transactions costs associated with engaging in physical arbitrage activity. It is only large discrepancies then between p_{it} away from p_{jt}–or correspondingly, in terms of (3), only large values for ε_t in absolute terms–that generate any real arbitrage activity. The thinking is that when prices are within a so called transactions cost band, a reasonable expectation then is that (5) might look very much like a unit root process, that is:

$$\Delta y_t \;=\; \delta_0 + \sum_{k=1}^{p} \phi_k \Delta y_{t-k} + \varepsilon_t. \tag{7}$$

Alternatively, if the difference between p_{it} away from p_{jt} is sufficient to cover typical transactions costs, then we would expect arbitrage activity to occur quickly, therefore bringing the spatially related prices back into line. In this case the model in (2) would apply where we would expect the estimate of ρ to be considerably less than zero, implying a relatively rapid return to within the transactions cost ban.

In terms of modeling price behavior that is consistent with a transactions cost ban, we could think of taking a weighted average of (5) and (7), given by:

$$\begin{aligned}\Delta y_t \;=\; & \left(\delta_{01} + \sum_{i=1}^{p} \phi_{i1} \Delta y_{t-i}\right)\left(1 - I\left(s_t, \boldsymbol{\theta}\right)\right) \\ & + \left(\delta_{02} + \sum_{i=1}^{p} \phi_{i2} \Delta y_{t-i} + \rho y_{t-1}\right) I\left(s_t, \boldsymbol{\theta}\right) + \varepsilon_t,\end{aligned} \tag{8}$$

where $\boldsymbol{\theta} = (\theta_1, \theta_2)'$ typically denotes a (2×1) parameter vector that defines the transactions cost band; $I(s_{t-1}, \boldsymbol{\theta})$ is a Heaviside indicator function such that $I(s_t, \boldsymbol{\theta}) = 0$ if $\theta_1 \leq s_t \leq \theta_2$ and $I(s_t, \boldsymbol{\theta}) = 1$ otherwise; and where s_t is the so called transition variable. In practice it is often the case that $s_t = y_{t-1}$, or perhaps y_{t-d} for some

$d \in [1, D_{max}]$, although it is also possible, as described by Kilian and Taylor (2003), to use a weighted average of lagged values of y_t. For example,

$$s_t = \left(\tfrac{1}{D_{max}}\right) \sum_{k=1}^{D_{max}} s_{t-k}, \tag{9}$$

could also be used as a candidate for the transition variable. The setup described in (8) yields what is referred to as the self exciting threshold autoregressive model, or SETAR model (see, e.g., Tong and Lim, 1980). Models of this sort have been used extensively in recent years to examine issues related to the LOP and, relatedly, Purchasing Power Parity (PPP). See, Lo and Zivot (2001), Goodwin, Grennes and Craig (2002), and Serra and Goodwin (2004), among others, for relevant applications of SETAR models involving the LOP.

As an alternative to the SETAR, various authors including, for example, Kilian and Taylor (2003), Ghoshray (2010), and Goodwin, Holt and Prestemon (2011) have proposed replacing the Heaviside indicator function, $I(s_{t-1}, \boldsymbol{\theta})$, in (8) with a specification that is continuous in s_t. For example, $I(s_{t-1}, \boldsymbol{\theta})$ could be replaced with:

$$G\left(s_t; \theta\right) = 1 - \exp\left(-\gamma\left(s_t - c\right)^{2\kappa}\right), \ \gamma > 0, \ \kappa = 1, 2, \ldots, \kappa_{max}, \tag{10}$$

where $\boldsymbol{\theta} = (\gamma, c, \kappa)'$ is a parameter vector. The combination of (10) and (8) yields the so called Generalized Exponential Smooth Transition Autoregression, or GESTAR, first considered by Goodwin, Holt and Prestemon (2011). The GESTAR is, in turn, an extension of the Exponential Smooth Transition Autoregression, or ESTAR, wherein $\kappa = 1$. In any event, the GESTAR model is a member of the general class of smooth transition autoregressive models, or STAR models, introduced by Teräsvirta (1994). In (10) γ is the speed–of–adjustment parameter, and in turn dictates how quickly the function moves from zero to one as s_t diverges from the centrality parameter, c, in absolute value. Likewise, κ is a shape parameter that determines how abrupt the transition is as $\sqrt{(s_t - c)^2}$ becomes large. Specifically, for large γ and large κ the GESTAR will approximate the SETAR model outlined previously. In practice $\kappa_{max} = 8$ is often sufficient to generate something akin to SETAR–like behavior, and therefore a typical search over κ might be conducted over the $\kappa \in [1, \ldots, 8]$ grid.

An alternative to the GESTAR is the generalized logistic function, given by:

$$G\left(s_t;\boldsymbol{\theta}\right) = \left[1+\exp\left(-\gamma\prod_{i=1}^{k}\left(s_t-c_k\right)\right)\right]^{-1}, \ \gamma>0, c_1\leq\ldots\leq c_k. \qquad (11)$$

When (11) is combined with (8), the resultant model is referred to as the Generalized Logistic Function Smooth Transition Autoregression, or GLSTAR. Two common choices for k are $k=1$ and $k=2$. When $k=1$ in (11), the generalized logistic function reduces to the standard two–parameter logistic function, which in turn, when combined with (8), generates the Logistic STAR, or LSTAR. While the LSTAR is useful for modelling certain types of nonlinearity, for example, the change in unemployment dynamics during expansions versus contractions (see, e.g., Skalin and Teräsvirta, 2002), it is generally not useful for modelling the role of transactions costs in the LOP. Alternatively, when $k=2$ the resultant transition function, when combined with (8), is the so called Quadratic STAR, or QSTAR model, which has also been used in LOP studies; see, for example, Goodwin, Holt and Prestemon (2011). The QSTAR, like the GESTAR, also implies equilibrium band behavior. Notably, as $\gamma\to\infty$, the quadratic logistic in (8) effectively becomes a Heaviside indicator function. In this manner the QSTAR also nests the popular SETAR specification, and therefore provides considerable flexibility in modeling.[4]

4 An Alternative Approach: Time–Varying Parameters

4.1 Time–Varying Autoregressions: Model Specification

Regardless of the approach used, the SETAR/STAR modelling framework that allows for the possibility of transactions costs, and thereby allows for estimated half–lives to be regime dependent, typically represents an improvement over the linear modelling approach in (3). Even so, the nonlinear framework assumes that markets are well established and that, moreover, institutional and technological changes have not occurred that would otherwise influence the ability to arbitrage the markets in question.

[4] Alternatively, in (11) when $k=1$, the resultant transition function when combined with (8) yields the Logistic STAR, or LSTAR model, which is also popular in applied work. See van Dijk, Teräsvirta and Franses (2002) for additional details.

As previously mentioned, this may not be the case for regional egg markets during the period of the late 19th and early 20th centuries. In this scenario a different modelling strategy may be in order.

As previously discussed, due to technological innovations in the late 19th century commercial refrigeration became not only technologically feasible but economically viable. As such, the ability to store eggs, even for comparatively brief periods of time, might have impacted the rapidity with which changes in relative prices would be arbitraged away. To this end the spatial price model in (8) could me modified so that $I(s_t, \boldsymbol{\theta})$ could be replaced with $I(t^*, \boldsymbol{\theta})$, where $t^* = t/T$, $t = 1, \ldots, T$. For example, if only the intercept is allowed to change, and if $\boldsymbol{\theta} = \theta$, a scalar, then we have:

$$\Delta y_t \; = \; \delta_{01} \left(1 - I\left(t^*, \theta\right)\right) + \delta_{02} I\left(t^*, \theta\right) + \sum_{i=1}^{p} \phi_i \Delta y_{t-i} + \rho y_{t-1} + \varepsilon_t, \qquad (12)$$

where $I(t^*, \boldsymbol{\theta})$ is a Heaviside indicator function such that $I(t^*, \boldsymbol{\theta}) = 0$ if $t^* \leq \theta$ and $I(t^*, \boldsymbol{\theta}) = 1$ otherwise. Models of this sort, that is, models that allow for a single, discrete break have been explored in detail by Perron (1989) and Andrews and Ploberger (1994), and extended to multiple discrete intercept breaks by Bai and Perron (1998, 2003).

While generalizing to models that allow for one or more intercept breaks is potentially useful, such models are likely of limited interest in the present context. Importantly, it is more likely that the structural change associated with the adoption of large–scale mechanical refrigeration over the period examined resulted in changes to the model's entire dynamic structure. Moreover, it is likely that construction and adoption of mechanical refrigeration during the period examined did not happen in strict zero–one manner, that is, with the structural shift occurring fully at single, precise point in time. To this end, a framework for model specification and estimation that is similar in spirit to the Bai and Perron methodology, but allows instead for the possibility of smoothly changing parameters–including persistence parameters–was put forth by Lin and Teräsvirta (1994).

The Lin and Teräsvirta approach is to use versions of either the generalized exponential function in (10) or the generalized logistic function in (11) where, as previously indicated, $s_t = t^*$. When combining these time–dependent transition functions with

(8), we obtain:

$$\begin{aligned}\Delta y_t \; = \; & \left(\delta_{01} + \sum_{i=1}^{p} \phi_{i1} \Delta y_{t-i} + \rho_1 y_{t-1}\right) \left(1 - G\left(t^*, \boldsymbol{\theta}\right)\right) \\ & + \left(\delta_{02} + \sum_{i=1}^{p} \phi_{i2} \Delta y_{t-i} + \rho_2 y_{t-1}\right) G\left(t^*, \boldsymbol{\theta}\right) + \varepsilon_t,\end{aligned} \tag{13}$$

the Time Varying Autoregression (TVAR). Of interest is that in this most general form all parameters in (13), including ρ, and hence the estimated half–life of a deviation from LOP equilibrium, can change in a potentially smooth manner over time. Moreover, if, the generalized logistic function in (11) is used with $k = 1$, and as $\gamma \to \infty$, the structural change becomes discrete at time $t^* = c$. In this manner the TVAR nests the discrete break methods put forth by Bai and Perron (1998). In this manner the general TVAR model offers considerable flexibility in modelling, and therefore is a potentially useful tool for examining changes in market price dynamics for eggs during a known period of rapid technological change.

4.2 Time–Varying Autoregressions: Testing and Model Specification

Before proceeding, several basic questions must be addressed. Specifically, in the first instance how do we know if a TVAR model is even called for? And how do we know if the TVAR model, once estimated, captures the relevant structural change? We now turn to addressing these issues.

To begin, the first question posed asks if the TVAR model in (13) is a statistically valid improvement in model fit relative to the constant parameter LOP model in (5). It would seem that such an issue could be addressed in a straightforward matter by simply estimating (13) and then performing a test of the hypothesis:[5]

$$\mathrm{H}_0 : \gamma \; = \; 0. \tag{14}$$

The problem with performing such a test, however, is that under the restriction implied by the null hypothesis the parameters $(\delta_{02}, \phi_{12}, \ldots, \phi_{p2}, \rho_2)'$ are not identified.

[5] Alternatively, setting $\delta_{01} = \delta_{02}, \phi_{11} = \phi_{12}, \ldots, \phi_{p1} = \phi_{p2}, \rho_1 = \rho_2$ also reduces (13) to a constant parameter model. In this case, the parameters in $\boldsymbol{\theta}$, namely, γ and c, are unidentified.

Problems of this sort, that is, tests wherein there are unidentified nuisance parameters under the null hypothesis, have been explored by Davies (1977, 1987). The implication is that usual test statistics such as the F–statistic associated with imposing the restrictions under the null hypothesis in (14) no longer have asymptotically valid F distributions.

Various methods have been proposed for circumventing this problem in the literature, including simulation methods (see, e.g., Hansen, 1997). Even so, a particularly useful approach in the present case, as described by Lukkonen, Saikkonen and Teräsvirta (1988), is to replace $G(t^*; \gamma, c)$ with a suitable Taylor series approximation, where the approximation is for γ evaluated at $\gamma = 0$. For example, a third–order Taylor series approximation yields, after substitution into (13) and collecting terms:

$$\Delta y_t \;=\; \boldsymbol{\beta}_0'\boldsymbol{x}_t + \boldsymbol{\beta}_1'\boldsymbol{x}_t t^* + \boldsymbol{\beta}_2'\boldsymbol{x}_t {t^*}^2 + \boldsymbol{\beta}_3'\boldsymbol{x}_t {t^*}^3 + \epsilon_t, \tag{15}$$

where $\boldsymbol{x}_t = (1, \Delta y_{t-1}, \ldots, \Delta y_{t-p}, y_{t-1})'$; where $\boldsymbol{\beta}_j$, $j = 0, \ldots, 3$ are conformable parameter vectors; and where ϵ_t includes the original error term, ε_t, plus approximation error. In this case a test of parameter constancy, that is, a test of (14), is akin to a test of the null hypothesis:[6]

$$\mathrm{H}_0' : \boldsymbol{\beta}_1 \;=\; \boldsymbol{\beta}_2 \;=\; \boldsymbol{\beta}_3 \;=\; \mathbf{0}. \tag{16}$$

Moreover, the test can be conducted by using the F–test version of an LM test, denoted as LM_0 , which under the null hypothesis of parameter constancy will be approximately F distributed with $3(p+2)$ and $T - 4(p+2)$ degrees of freedom.

Following a framework similar to that put forth by Teräsvirta (1994), Lin and Teräsvirta (1994) define a sequence of tests that, in principle, may be used to identify whether the GESTAR in (10) (or, alternatively, the QSTAR in (11) when $k = 2$) or the LSTAR in (11) (i.e., when $k = 1$) is called for. Specifically, the hypotheses to be tested are:

$$\begin{aligned} \mathrm{H}_{03} &: \boldsymbol{\beta}_3 \;=\; \mathbf{0} \\ \mathrm{H}_{02} &: \boldsymbol{\beta}_2 \;=\; \mathbf{0} \,|\, \boldsymbol{\beta}_3 \;=\; \mathbf{0} \\ \mathrm{H}_{01} &: \boldsymbol{\beta}_1 \;=\; \mathbf{0} \,|\, \boldsymbol{\beta}_2 \;=\; \boldsymbol{\beta}_3 \;=\; \mathbf{0} \end{aligned} \tag{17}$$

[6]Under the null hypothesis of parameter constancy there is no approximation error and hence $\epsilon_t = \varepsilon_t$.

Of course the testing sequence in (17) can be performed as a sequence of LM F tests similar to that described for the general test of nonlinearity in (16). The corresponding sequence of LM tests may be defined as: LM_{03}, LM_{02}, and LM_{01}. Finally, the basic parameter constancy test in (16) as well as the sequence of tests in (17) can be performed for all variables included in $\boldsymbol{x}_t$ or for some subset of variables. For example, suppose that both lagged values of Δy_t and seasonal dummy variables are included in the base model. With the hope of obtaining more parsimonious final model specifications, it may be desirable to test for parameter constancy separately for the lagged dependent variables and the seasonal terms.

In any event the basic idea underlying the testing sequence in (17) is simple, and is as follows. Assume that linearity is rejected, that is, that the null hypothesis in (16) is rejected. Then if H_{02} in (17) is associated with the smallest p–value, a second–order approximation apparently has the most empirical support, which in turn implies that the GESTAR in (10) or the QSTAR where $k = 2$ in (11) is called for.[7] Alternatively, if either H_{03} or H_{01} are associated with the smallest p–value in the testing sequence, then an LSTAR (i.e., (11) when $k = 1$) is suitable.[8] Once the candidate transition function has been identified, the parameters of the TVAR model may be estimated by using nonlinear least squares. See van Dijk, Teräsvirta and Franses (2002) for details on model estimation.

Once a candidate TVAR model has been identified and estimated it is useful to evaluate its statistical adequacy. To do so, define the skeleton of the relevant TVAR model as:

$$F(\boldsymbol{x}_t, \boldsymbol{\psi}) \;=\; \boldsymbol{\varphi}_1'\boldsymbol{x}_t\left(1 - G(t^*, \boldsymbol{\theta})\right) + \boldsymbol{\varphi}_2'\boldsymbol{x}_t G(t^*, \boldsymbol{\theta}), \tag{18}$$

where $\boldsymbol{\varphi}_i = (\delta_{0i}, \phi_{1i}, \ldots, \phi_{pi}, \rho_i)'$, $i = 1, 2$; where $\boldsymbol{\theta} = (\gamma, c)'$ with an LSTAR or GESTAR and $\boldsymbol{\theta} = (\gamma, c_1, c_2)'$ for the QSTAR; and where the vector $\boldsymbol{\psi}$ is defined as $\boldsymbol{\psi} = (\boldsymbol{\varphi}_1, \boldsymbol{\varphi}_2, \boldsymbol{\theta})'$. Let $\hat{\varepsilon}_t$ denote the estimated residuals from the TVAR. And let $\nabla F\left(\boldsymbol{x}_t, \hat{\boldsymbol{\psi}}\right) = \partial F(.)/\partial\boldsymbol{\psi}|_{\boldsymbol{\psi}=\hat{\boldsymbol{\psi}}}$, that is, let $\nabla F\left(\boldsymbol{x}_t, \hat{\boldsymbol{\psi}}\right)$ denotes the gradient of the skeleton of the TVAR model with respect to its parameters. Following Eitrheim and

[7]Discriminating between the GESTAR and the QSTAR cannot be done by testing, but rather must be done based on overall model fit and diagnostic criteria.

[8]Alternatively, Escribano and Jordà (1999) argue that expanding (16) to include fourth–order terms in the approximation can be useful when attempting to discriminate between a GESTAR/QSTAR and an LSTAR. The null hypothesis in (16) and, as well, in (17) would in this be modified accordingly.

Teräsvirta (1996), an LM test of remaining autocorrelation, referred to as LM_{AR}, can then be obtained by regressing $\hat{\varepsilon}_t$ on the elements in $\nabla F\left(\boldsymbol{x}_t, \hat{\boldsymbol{\psi}}\right)$ and q lags of $\hat{\varepsilon}_t$ and by then performing an F test for the joint significance of the lagged residual terms. In a similar manner, an LM test for remaining (additive) parameter non–constancy, referred to as LM_{TV} may be performed in a similar manner. Specifically, $\hat{\varepsilon}_t$ is regressed on elements in $\nabla F\left(\boldsymbol{x}_t, \hat{\boldsymbol{\psi}}\right)$ and the interaction terms $\boldsymbol{x}_t t^*$, $\boldsymbol{x}_t t^{*^2}$, and $\boldsymbol{x}_t t^{*^3}$, with the joint significance of the latter $3(2+p)$ terms tested in the usual manner by using an appropriate F test. Finally, as with the initial parameter constancy tests discussed previously, it is possible to: (1) perform a sequence of tests for remaining parameter non–constancy in a manner similar to that in (17) and, (2) to conduct tests for remaining parameter non–constancy on a subset of variables included in the initial model specification. See Eitrheim and Teräsvirta (1996) for additional details on diagnostic testing in the context of smooth transition models.

5 Data and Basic Data Properties

5.1 Overview

In the empirical analysis we analyze wholesale egg prices for nine U.S. cities, including: Baltimore (BWI), Chicago (CHI), Cincinnati (CVG), Dubuque (DBQ), Indianapolis (IND), Minneapolis (MSP), New Orleans (MSY), New York (NYC), and Saint Louis (STL). The data are taken from Holmes (1913) and are reported as monthly wholesale prices for eggs in cents/dozen. In most instances the sample period runs from October, 1880 through September, 1911 for a total of 372 monthly observations; in the case of Minneapolis, however, the data do not begin until October, 1983 for a total of 336 observations. Sample properties for the underlying city–level egg price data are summarized in the upper panel of Table 1. Likewise, time series plots for the egg price data are presented in Figure 1. As illustrated in Table 1, on average New York is associate with the highest average price over the sample period followed, respectively, by Baltimore and Chicago. These results are consistent with the notion that large, urban population centers were effectively net importers of eggs. Alternatively, the lowest average price is for Saint Louis followed by Indianapolis. These results also make sense inasmuch as both cities are centrally located in what has historically been (and continues to be) a prime agricultural production region of the United States. It is also of interest that prices in New York and Baltimore were also more volatile than those elsewhere, again a result consistent with these cities being net importers of eggs.

Prior to estimation all data are converted by taking natural logarithms, implying that, in a manner consistent with (3), that the primary variables of interest, that is, the y_t's, are log relative prices. It is common in LOP studies to choose one or more central markets as representative of the base price. For example, when using the same data we consider here Serra et al. (2006) treat New York as the central market. In the present analyses we treat the prices in New York and Chicago as the representative central markets. We use these respective cities to denote base prices because even during the time considered they were major population centers, and hence were likely regions that were consistent net importers of eggs from other regional markets. Moreover, Chicago, although likely a consistent net importer of eggs, is obviously closer in proximity to the central egg producing region than is New York.

Summary statistics for the log relative price pairs are reported in the lower panel of Table 1. Plots of the prices relative to the New York base are reported in Figure 2 while those for prices relative to the Chicago central market are presented in Figure 3. As indicated in both Table 1 and Figure 2, New York did indeed experience higher prices on average relative to markets in the interior. Even so there were obviously brief periods when prices in the interior exceeded those in New York. Also, as further illustrated in Table 1, egg prices in Chicago also tended to be higher than those in other regional markets (with Baltimore being a notable exception), but even so there were larger number of periods (relative to the case where New York in the base) where prices in Chicago were lower than those in other reginal markets. This general observation is made especially clear from the plots presented in Figure 3.

5.2 Basic Data Properties

As an initial step in the analysis, we being by exploring some of the basic time series properties of the data. First, we conducted standard unit root tests for each nominal series and concluded that, with the exception of Indianapolis, nominal wholesale egg prices in each city considered apparently has one autoregressive unit root. For this reason we exclude Indianapolis in all subsequent analyses involving relative prices. Next, we examined the time series properties of relative prices by treating New York and Chicago as the central markets for purposes of comparison.[9] That is, y_t is constructed either as the log of the egg price in New York relative to other cities or the log of the egg price in Chicago relative to other cities.

At this stage of the analysis two sets of additional tests are performed. Firstly, we test the log relative prices for a unit root by using a standard testing procedure, namely, Augmented Dickey–Fuller (ADF) tests wherein the relevant test statistics are bootstrapped.[10] Specifically, the model examined under the null of a unit root in the present case is:

$$\Delta y_t \;=\; \delta_0 + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \sum_{j=1}^{11} \pi_i D_{jt} + \varepsilon_t, \tag{19}$$

where D_{jt} are monthly dummy variables defined as $D_{jt} = S_{jt} - S_{12t}$, $j = 1, \ldots, 11$, and where S_{jt} are standard monthly dummy variables.[11] Note that while in general the LOP would rule out the inclusion of predictable seasonality, it is likely the case that, due in part to technical change associated with mechanical refrigeration, that seasonal price patterns changed during the sample period. Moreover, it is also likely the case that the rate of change in seasonality differed by geographic region. For this reason we include seasonal terms in all LOP regressions. When parameter constancy is assumed, the alternative to (19) is simply a model wherein y_{t-1} is included as an additional regressor. The bootstrap tests are performed then by estimating the appropriate models under both the null and the alternative, constructing the test statistic (i.e., the t–statistic associate with the coefficient on y_{t-1}), and then dynamically boostrapping the residuals of the null model in (19) 999 times. For each bootstrap draw the alternative model is also estimated and the relevant test statistic obtained and stored. The empirical p–value of the sample test can then be constructed by using

[9] In a related study, Serra et al. (2006) examined only New York as the candidate central market.

[10] The bootstraps are dynamic bootstraps of the null model, that is, the model that contains a unit root process.

[11] The specification for D_{jt} allows for separate interpretation of the intercept term, and therefore does not alter the interpretation of δ_0 as a drift parameter under the null of a unit root.

the constructed empirical sampling distribution.

The results of the linear unit root tests for the relevant city price pairs are recorded in the left–hand panel of Table 2. For testing purposes optimal lag lengths, p, are determined by using Akaike's (1974) information criterion, or AIC. As results in the Table indicate, the null of a unit root, and therefore mean reversion, is rejected at usual significance levels for all city pairs except for New York and Cincinnati, where the empirical p–value is 0.128. At this point there appears to be substantial evidence in support of the LOP for late 19th and early 20th century regional egg markets in the United States. In other words, there is empirical evidence that virtually all of the markets considered were reasonably well integrated. Even so, these tests do not allow for the possibility of structural change, the issue to which we now turn.

What is desirable in the present case is to test the null of a unit root as depicted by the model in (19) against the TVAR alternative with mean reversion as illustrated in (13). Of course such a direct test is not possible in the present case because of the problems already noted with unidentified nuisance parameters under the null hypothesis. One possibility, however, is to use in lieu of (13) the approximating regression in (15). In this case the approximating regression fully nests the null model in (19), and an F–test statistic of the restrictions involved can be readily computed. Specifically, define $\widetilde{\boldsymbol{x}}_t = (\Delta y_{t-1}, \ldots, \Delta y_{t-p}, D_{1t}, \ldots, D_{11t})'$, so that $\boldsymbol{x}_t = (1, \widetilde{\boldsymbol{x}}_t, y_{t-1})'$. We may then re–write (15) as:

$$\Delta y_t \; = \; \beta_0 + \boldsymbol{\vartheta}_0' \widetilde{\boldsymbol{x}}_t + \lambda_0 y_{t-1} + \sum_{j=1}^{3} \beta_j t^{*^j} + \sum_{j=1}^{3} \lambda_j y_{t-1} t^{*^j} + \sum_{j=1}^{3} \vartheta_j' \widetilde{\boldsymbol{x}}_t t^{*^j} + \epsilon_t, \tag{20}$$

where as before ϵ_t contains both the original error, ε_t, and approximation error. The relevant null hypothesis of linearity *and* a unit root in this case is then: H_0^{lur} : $\lambda_0 = \beta_1 = \beta_2 = \beta_3 = \lambda_1 = \lambda_2 = \lambda_3 = \vartheta_{1,1} = \ldots = \vartheta_{3,p+11} = 0$. We denote the corresponding F statistic as F_{lur}, where lur is short for 'linear unit root'. In general F_{lur} will be associated with $(7 + 3\,(p + 11))$ and $T - (8 + 4\,(p + 11))$ degrees of freedom, respectively. The problem in the present case, however, is that for the usual reasons F_{lur} is not associated with a standard F distribution under the null hypothesis. Even so, as argued by Eklund (2003) and illustrated by Balagtas and Holt (2009), it is possible under many circumstances to simply employ a dynamic bootstrap for which the empirical distribution of the F_{lur} test statistic can be generated. Such a procedure is, in fact, what we do here.

The results of testing a linear unit root model against mean reversion with structural change are presented in the center panel of Table 2. The results essentially confirm those of the linear unit roots tests discussed previously. Of some interest is that in this instance for the New York–Cincinnati price pair the null hypothesis of linearity and parameter constancy is rejected at the 10–percent level, but not at the 5–percent level. On balance the results of these tests suggest that estimation of the general TVAR model in (13) may be valid for most if not all price pairs considered.

As a final test of the general properties of the city price–pairs, the null hypothesis of parameter constancy was tested against the alternative of a TVAR by computing the LM_0 test statistic. Specifically, for testing parameter constancy we assume that mean reversion occurs under the null hypothesis. Although, as described previously, this test statistic is distributed approximately as an F with $3\,(p+2)$ and $T-4\,(p+2)$ degrees of freedom, for completeness we obtain bootstrapped p–values for this test statistic as well. The results are reported in the right–hand panel of Table 2. There we see in most instances there is reasonably strong evidence of parameter non–constancy for relative egg prices consistent, perhaps, with a TVAR specification. The lone exception appears to be the Chicago–Dubuque price pair. Given that Dubuque is 178 miles from Chicago, and given that these cities were likely highly interconnected by rail throughout the sample period, it is likely the case that the adoption of refrigeration made little difference at the margin to the price relationship for eggs in these two cities.

6 Model Specification and Estimation Results

6.1 Additional Parameter Constancy Test Results

The preliminary results discussed in the previous section suggest that parameter non–constancy may be a feature of the city price pairs in a number of instances. As a further aid to specifying the appropriate pattern of structural change in the TVAR models, the testing sequence outlined in Section 4.2 was employed. The analysis begins by estimating for each city pair an appropriate linear autoregressive (AR) model of the general form:

$$\Delta y_t \ = \ \delta_0 + \sum_{i=1}^{p} \varphi_i \Delta y_{t-i} + \rho y_{t-1} + \sum_{j=1}^{11} \pi_i D_{jt} + \varepsilon_t,$$

which differs from the specification in (19) in that the lagged level term, y_{t-1}, is included. As well, the lag order, p, is determined by using the Hannan and Quinn (1979) information criterion, or HQC.[12] Once estimated, the residuals from the linear models can be used to perform the sequence of tests outlined in 16 and (17). The testing sequence is, in turn, applied to: (1) the intercept; (2) the lagged dependent variable terms, or model synamics; and (3) the seasonal dummy variable terms. The results are reported in Table 3.

There are several noteworthy results in Table 3. To begin, there are only three city pairs (i.e., New York–New Orleans, Chicago–Dubuque, and Chicago–New Orleans) for which there is no significant evidence of structural change in the linear AR model's dynamics. In fact, as indicated previously in Table 2 the results in Table 3 provide further confirmation that the Chicago–Dubuque price pair experienced no significant structural change in any facet of the model during the 1880–1911 sample period. For these reasons we do not further pursue any investigation of the Chicago–Dubuque price relationship. Even so, we note that the estimated half–life associated with a deviation from the LOP for the Chicago–Dubuque city pair is 0.400, or approximately twelve days. This suggests a high degree of market integration between Dubuque and Chicago and a degree of integration, which, moreover, is stable throughout the sample period. This result is perhaps not surprising given that Dubuque was a primary feeder market for farm products from Iowa and other western regions of the so called Corn Belt.

Regarding the New York–New Orleans and Chicago–New Orleans results, given the relative distances involved it is perhaps not surprising that there is no evidence of structural change in their respective dynamics. The estimated half–lives are, accord-

[12]The HQC tends to be more parsimonious than the AIC, which is potentially useful when fitting TVAR models. Moreover, once a provisional model is fitted to the data LM tests may be performed to determine if there is significant remaining autocorrelation.

ingly, 1.56 months (46.67 days) and 0.966 months (29 days). While physical trade data among these cities do not, to our knowledge, exist, the results suggest that only limited trade in eggs occurred between the Northeast (Midwest) and New Orleans. While in both instances, that is, for both NYC–MSY and CHI–MSY, there is some evidence that seasonal patterns changed over time, we do not investigate this issue further.

For the remainder of the city pairs reported on in Table 3, there is ample evidence of structural change in each respective model's dynamics. In most of these instances the structural change appears to be consistent with an LSTAR specification. The sole exception is for the Chicago–Minneapolis price pair, where it seems that the model's dynamics change over time in a manner consistent with the GESTAR. In most instances there is also evidence of evolving seasonal patterns in the price pairs, with the exceptions being New York–Chicago, New York–Dubuque, and New York–Minneapolis.

6.2 TVAR Models

The results in Table 3 are used as a guide for specifying provisional TVAR models for the nine city pairs for which structural change in the model's autoregressive terms was suggested. In each case a provisional TVAR model was estimated and evaluated by using, notably, the diagnostic tests described in Section 4.2. Importantly, diagnostic tests for parameter constancy in each provisional TVAR were preformed for, respectively, the intercept, the autoregressive terms, and the seasonal terms. The results of these tests along with the results of the LM tests for remaining serial correlation were used in a number of instances to further refine the TVAR specifications. The estimation along with a suite of model diagnostic test results for the final TVAR specifications are reported in Table 4. Plots of the estimated transition functions are presented in Figure 4.

In estimation we employ the parametrization for γ suggested by Goodwin, Holt and Prestemon (2011), where instead of estimating γ directly instead η is estimated in the identity $\gamma = \exp(\eta)$. This transformation tends to provide for greater numerical stability in the estimation of the speed–of–adjustment parameter. Following common practice (see, e.g., van Dijk, Strikholm and Teräsvirta, 2003), in estimation we also impose an upper limit on η. Specifically, we bound η from about at 5.010635, which corresponds to a value of 150 for γ.[13] Finally, because γ is not *per se* scale free, we divide it by the "standard deviation" of $t^* = t/T, t = 1, \ldots, T$, which we denote by $\hat{\sigma}_{t^*}$. See Teräsvirta, Tjøstheim and Granger (2010) for additional details.

For each city pair considered there is only one transition function associated with the TVAR model's dynamics, that is, with its autoregressive structure. Moreover, for all city pairs save for Chicago–Minneapolis, the corresponding transition function is of the simple logistic type, that is, of the type identified in (11) where k is set to one. The implication is, depending on the magnitude of the speed–of–adjustment parameter, γ, that the change in the autoregressive structure, and hence, in implied half lives, can be either sharp or gradual. In the case of Chicago–Minneapolis, and consistent with the results in Table 3, a generalize exponential transition function was specified to accommodate the structural change in the model's dynamics. That is, (10) was employed where $\kappa = 4$ was found to provide the best overall fit. In only one case, namely, for New York–Chicago, were three transition functions needed to capture relevant structural change. In the remainder of the cases considered either two (i.e., New York–Cincinnati, Chicago–Baltimore, Chicago–Cincinnati, and Chicago–Minneapolis) or one (i.e., New York–Dubuque, New York–Minneapolis, New York–St. Louis, and Chicago–St. Louis) were included in the relevant TVAR.

The diagnostic test results recorded in Table 4 show that in all instances the estimated TVAR models provide a reasonable good fit to the data, especially after considering that the dependent variable is in each case in first difference form. The results also show, as indicated by the ratio of the residual standard error for the TVAR model ($\hat{\sigma}_{NL}$) relative to that of the fixed–parameter AR model ($\hat{\sigma}_L$), that each estimated TVAR model yields an improvement in fit relative to its fixed–parameter counterpart. The results further reveal there is in no evidence of remaining residual autocorrelation at lags four or twelve for any of the estimated TVAR models, therefore implying there is no misspecification of each model's dynamic component. Importantly, in

[13] As indicated previously, for large values of $\gamma = \exp(\eta)$ the transition function effectively becomes a Heaviside indicator function. Convergence of the nonlinear estimation algorithm in this case can be difficult to obtain as the derivatives of the likelihood function with respect to η parameter will typically become degenerate. For this reason it is common practice to place an upper limit on this parameter in estimation.

every case LM diagnostic tests indicate there is no evidence of remaining parameter non–constancy with respect to each estimated model's autoregressive parameters. In several instances there is some evidence of remaining parameter non–constancy for the intercept and/or seasonal terms, but given that these parameters are not involved in determining estimates of time–varying half lives, we did not pursue these issues further. Finally, the results in Table 4 indicate that in most cases the residuals for the estimated TVAR depart significantly from the normality assumption, typically due to fat–tailed behavior (i.e., a larger number of outliers than would be suggested by the normal distribution). The basic picture revealed in Table 4, however, is that (1) the estimated TVAR models provide a reasonable fit to the data; and (2) the diagnostic test results indicated only limited evidence of model misspecification.

Of interest, of course, is the nature of the structural change implied by each estimated TVAR model. Plots of the estimated transition functions for each TVAR are reported in Figure 4. As indicated there the majority of the estimated transition functions were of the simple logistic function type, that is, consistent with (11) where $k = 1$. In three cases, however, structural change appears to have been U–shaped, that is, of the generalized exponential form in (10). Even so, only for the Chicago–Minneapolis price pair does the model's autoregressive structure evolve in a manner consistent with the generalized exponential form.

To obtain additional information, the timing of structural change in the autoregressive structure for each estimated TVAR model is detailed in Table 5. As indicated there (as well as in the results in Figure 4), of the eight TVARs with dynamics that evolve according to a simple logistic function, four effectively have nearly instantaneous adjustments, that is, $ga\hat{m}ma = 150$ (i.e., New York–Cincinnati, New York–Minneapolis, Chicago–Baltimore, and Chicago–Cincinnati). The remaining four TVARs experience more gradual structural change, as indicated in Table 5. Of additional interest is that while there is some variation in the dates around which structural change in the each model's dynamics is centered, with only two exceptions (i.e., for New York–St. Louis and for Chicago–Cincinatti) the structural change is centered at some point in the 1890s. And even for the two exceptions the change is centered at dates occurring in the very early 1900s. Although the exact timing of the construction and implementation of mechanical refrigeration in the cities considered is unknown, casual evidence suggests that the dates corresponding the midpoint of structural change are not inconsistent with the adoption of large–scale mechanical refrigeration.

6.3 Half Life Estimates

As noted previously, a key component of the present analysis is an assessment of the half–life trajectory associated with a shock to the underlying price relationship. Specifically, the estimated half–life defines the horizon, h, at which at which the effect of a shock is one–half as prices adjust back to the long–run LOP equilibrium. Based on (6), we define the estimated half–lives over time for a TVAR model as:

$$\hat{h}\left(t^{*}\right) \;=\; \frac{\ln\left(0.5\right)}{\ln\left(1+\hat{\rho}_{1}\left(1-G\left(t^{*};\hat{\gamma},\hat{c}\right)\right)+\hat{\rho}_{2}G\left(t^{*};\hat{\gamma},\hat{c}\right)\right)}, \tag{21}$$

where $\hat{\rho}_1$ and $\hat{\rho}_2$ are the estimates of ρ_1 and ρ_2 based on (13) and where $G\left(t^{*};\hat{\gamma},\hat{c}\right)$ is the estimated transition function. Implicit in the definition of (21) is the assumption that $\hat{\rho}_j \in (0,1)$ in order for $\hat{h}\left(t^{*}\right)$ to be continuously defined. Moreover, while (21) provides an estimate of the mean–path for the half–lives implied by an estimated TVAR, it is also possible to use, for example, a delta method approximation to obtain an approximate 90–percent confidence interval associated with the mean estimates, say, $\left(\hat{h}_{l}\left(t^{*}\right),\hat{h}_{u}\left(t^{*}\right)\right)$. See, for example, Rossi (2005) for additional details and discussion.[14] Finally, for ease of presentation and interpretation we convert estimated half–lives, which in the present case will naturally be reported in fractions of months, to days by multiplying all estimates by 30.4375.

Mean paths for estimated half–lives along with approximate 90–percent confidence intervals are presented in Figure 5. What is revealed is that in every case estimated half–lives increase toward the end of the sample relative to the beginning of the sample. Likewise, in most instances the estimated confidence interval limits also widen following the structural change. For example, the estimated half–life for the New–York Chicago price pair is approximately 7.96 days (with an estimated standard error of 2.22 days) in the early and mid 1880s, but increases to 53.5 days (with a standard error of 10.88 days) by the end of the sample (September of 1911). Similarly, for the Chicago–St. Louis price pair the estimated half–life is approximately 7.87 days

[14] Because half–lives cannot be negative, we follow common practice (see, e.g., Rossi, 2005) and, when necessary, truncate the lower confidence interval at zero.

through the 1880s (with an approximate standard error of 6.05 days) to 57.60 days (with an approximate standard error of 17.71 days) towards the end of the sample period. Similar results are evident for the remaining price pairs considered.[15]

At first blush these results seem counterintuitive. Why, for example, would technical change that is presumably linked to the adoption of mechanical refrigeration result in an increase in the half–life of a shock? Further reflection, however, reveals that these results make intuitive sense. Prior to the adoption of mechanical refrigeration, and due to the perishability of commodity in question, egg wholesalers had no choice but to sell (ship) their egg inventory as quickly as possible. But following the adoption of mechanical refrigeration, wholesalers now could consider a temporal as well as a spatial dimension to egg marketing. For example, the ability to store eggs for even one or two weeks could, at the margin, could have a significant impact on spatial price relationships. This appears to be the case here with regional markets, at the margin, becoming somewhat less integrated over space following a period of rather extreme and rapid technical change.

7 Conclusions

With the wide–scale adoption of natural and mechanical refrigeration in the shipping and storage of perishable commodities in the late–nineteenth century, U.S. egg production expanded dramatically. This expansion was promoted by the spatial integration of the market for eggs. Simply put, farmers could now profitably ship their eggs to a wider array of markets, which collectively increased the size of the market. At the same time, mechanical refrigeration permitted farmers and wholesalers to store eggs for future consumption in local, or at least less–distant, urban areas, and thus sellers could arbitrage over time as well as space.

We find that, in general, the half–lives of a price shock for a wide range of market pairs actually increased following the adoption of refrigeration. At first glance, this result seems to conflict with the results from the spatial integration literature. Indeed,

[15] As indicated in Table 4, the estimate of ρ_1 for the Chicago–Minneapolis price pair is -1.029. This result implies effectively instantaneous returns to the LOP following a price shock when $G_2 = 1$, which in this case occurs between 1887.06 and 1892.10.

they suggest that refrigeration disrupted the market for eggs and, thus, led to a loss in welfare. We argue, however, that such an interpretation ignores the temporal dynamics of the market for perishables. For example, an Ohio wholesaler, who, having access to refrigerated shipping in the 1880s might have sold his inventory in New York, as long as the New York price covered his variable costs, rather than see it rot in Ohio, could, with access to a mechanically refrigerated storage facility, simply hold the inventory in Ohio until prices increased, perhaps in a few weeks. Such a transaction would tend to weaken the spatial bond between Ohio and New York, but it would be welfare–enhancing from the perspective of the economy overall. Although we have not estimated the welfare effects of the resulting temporal price dynamics, we suspect they would be represent a substantial proportion of the roughly 1.25 percent increase in national income Craig, Goodwin and Grennes (2004) attributed to the adoption of refrigeration in the shipping of perishables more generally.

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Table 1: Basic Descriptive Statistics For U.S. City Egg Prices: Raw Data and Log Relative Prices.

City	Variable	T	Mean	StDev	Min	Max
Baltimore	BWI	372	19.47	6.03	9.25	40.00
Chicago	CHI	372	17.31	5.42	8.00	37.50
Cincinnati	CVG	372	16.56	5.87	7.00	40.00
Debuque	DBQ	372	16.29	5.41	7.25	37.50
Indianapolis	IND	372	15.60	5.34	7.00	35.00
Minappolis	MSP	336	16.58	5.42	7.25	38.00
New Orleans	MSY	372	16.45	5.29	7.00	33.50
New York	NYC	372	22.72	7.32	10.38	46.00
St. Louis	STL	372	15.37	5.25	6.00	38.00
	log(NYC/CHI)	372	26.99	13.11	-15.08	79.85
	log(NYC/CVG)	372	32.50	12.53	-5.13	76.21
	log(NYC/DBQ)	372	33.59	16.29	-24.61	87.55
	log(NYC/IND)	372	38.16	12.68	0.00	86.50
	log(NYC/MSP)	336	30.96	15.58	-18.76	107.61
	log(NYC/MSY)	372	32.46	16.06	-12.41	91.63
	log(NYC/STL)	372	39.82	14.63	-2.02	98.08
	log(CHI/BWI)	372	-11.87	11.38	-54.36	30.11
	log(CHI/CVG)	372	5.51	13.76	-30.23	59.14
	log(CHI/DBQ)	372	6.59	12.07	-36.55	51.88
	log(CHI/IND)	372	11.16	11.09	-24.12	54.52
	log(CHI/MSP)	336	3.49	12.14	-32.38	47.00
	log(CHI/MSY)	372	5.46	16.54	-51.08	57.98
	log(CHI/STL)	372	12.83	12.26	-36.77	57.38

Note: Raw prices are reported in cents per dozen. T denotes the effective sample size; Mean denotes the sample average; StDev denotes the sample standard deviation; Min denotes minimum observation in the sample; and Max denotes the maximum observation in the sample. The lower panel reports basic statistics for log relative prices, in each case multiplied by 100.

Table 2: Unit Root and Parameter Constancy Test Results for Relevant City Price Pairs.

	Linear Alternative		Nonlinear Alternative, F_{lur}		TVAR Alternative, LM_0	
City Pair	Test Statistic	p–value	Test Statistic	p–value	Test Statistic	p–value
NYC-CHI	-5.909	0.001	2.604	0.001	1.802	0.003
NYC-CVG	-2.375	0.128	1.555	0.081	1.490	0.049
NYC-DBQ	-5.503	0.001	2.474	0.001	1.851	0.002
NYC-MSP	-4.354	0.001	2.099	0.003	1.779	0.003
NYC-MSY	-4.035	0.003	1.603	0.039	1.316	0.050
NYC-STL	-7.754	0.001	3.636	0.001	2.169	0.001
CHI-BWI	-7.344	0.001	2.999	0.001	1.677	0.010
CHI-CVG	-6.442	0.001	2.733	0.001	1.775	0.003
CHI-DBQ	-6.391	0.001	1.781	0.014	1.013	0.420
CHI-MSP	-4.761	0.001	2.172	0.001	1.527	0.014
CHI-MSY	-6.086	0.001	2.104	0.002	1.339	0.057
CHI-STL	-6.439	0.001	3.550	0.001	2.518	0.001

Note: p–values are empirical p–values obtained by conducting 999 dynamic boostrap replications. In each case the optimal lag length, p, is determined by using Akaike's (1974) information criterion, or AIC. For the parameter non–constancy test, LM_0, the null model is one for which mean reversion is maintained.

Table 3: Results of Lagrange Multiplier Parameter Constancy Tests Applied to the Model's Intercept, Lagged Dependent Variables, and Seasonal Terms.

City Pair	Intercept				Dynamics				Seasonals			
	LM_0	LM_{03}	LM_{02}	LM_{01}	LM_0	LM_{03}	LM_{02}	LM_{01}	LM_0	LM_{03}	LM_{02}	LM_{01}
NYC-CHI	$\mathbf{2.01\times10^{-3}}$	0.727	0.616	$\underline{2.45\times10^{-4}}$	$\mathbf{5.80\times10^{-6}}$	0.035	0.850	$\underline{6.72\times10^{-7}}$	0.146	0.173	0.213	0.047
NYC-CVG	$\mathbf{7.68\times10^{-3}}$	0.655	0.137	0.365	$\mathbf{4.56\times10^{-3}}$	0.195	0.513	$\underline{9.07\times10^{-4}}$	$\mathbf{6.94\times10^{-4}}$	0.389	$\underline{4.72\times10^{-10}}$	0.026
NYC-DBQ	$\mathbf{1.47\times10^{-4}}$	0.718	0.505	$\underline{1.70\times10^{-5}}$	$\mathbf{1.20\times10^{-5}}$	0.059	0.905	$\underline{1.00\times10^{-6}}$	0.087	0.428	3.81×10^{-3}	0.015
NYC-MSP	$\mathbf{1.31\times10^{-3}}$	0.202	0.320	$\underline{2.44\times10^{-3}}$	$\mathbf{1.00\times10^{-3}}$	0.127	0.138	$\underline{1.06\times10^{-3}}$	0.086	0.613	1.03×10^{-6}	0.335
NYC-MSY	**0.014**	0.130	0.835	$\underline{4.45\times10^{-3}}$	0.194	0.588	0.463	0.063	**0.045**	0.353	$\underline{1.25\times10^{-4}}$	0.270
NYC-STL	0.313	0.270	0.913	0.130	$\mathbf{1.03\times10^{-3}}$	0.468	0.497	$\underline{5.29\times10^{-5}}$	$\mathbf{2.29\times10^{-3}}$	0.842	5.8E-05	$\underline{1.08\times10^{-4}}$
CHI-BWI	0.748	0.742	0.859	0.320	**0.036**	0.091	0.423	$\underline{0.035}$	**0.016**	0.103	$\underline{2.96\times10^{-5}}$	0.040
CHI-CVG	**0.014**	0.513	0.339	$\underline{0.017}$	**0.010**	0.029	0.815	$\underline{8.42\times10^{-3}}$	**0.011**	0.746	$\underline{1.41\times10^{-5}}$	3.82×10^{-3}
CHI-DBQ	0.994	0.876	0.939	0.849	0.129	0.012	0.999	0.291	0.564	0.561	0.027	0.265
CHI-MSP	**0.012**	$\underline{0.015}$	0.333	0.255	**0.010**	0.862	$\underline{6.18\times10^{-3}}$	0.063	**0.035**	0.414	$\underline{1.21\times10^{-9}}$	0.321
CHI-MSY	0.305	0.060	0.885	0.954	0.263	0.057	0.374	0.681	$\mathbf{9.05\times10^{-3}}$	0.033	$\underline{5.35\times10^{-5}}$	0.055
CHI-STL	**0.031**	0.217	0.692	$\underline{0.010}$	$\mathbf{1.29\times10^{-3}}$	0.137	0.657	$\underline{1.81\times10^{-4}}$	$\mathbf{1.00\times10^{-3}}$	0.519	9.77×10^{-4}	$\underline{3.34\times10^{-5}}$

Note: Entries are p–values for LM tests of parameter constancy including the testing sequence defined in (17). In each case the misspecification tests are applied to a linear AR model. A bolded entry in the column headed LM_0 indicates that the null hypothesis of parameter constancy is rejected at the 5–percent level. An underlined entry in the corresponding LM_{03}, LM_{02}, and LM_{01} columns indicate the minimum p–value in the testing sequence. If the LM_{03} or LM_{01} p–values are underlined an LSTAR specification is called for. Alternatively, if the LM_{02} p–value is underlined a GESTAR transition function is in order.

Table 4: TVAR Model Estimates for the Monthly Regional Egg Price Relationships, 1881–1911.

Panel A, $y_t = ln(NYC_t/CHI_t)$

$$\Delta y_t = \underset{(0.022)}{0.140}[1 - G_1(t^*;\eta_1,c_1)] + \underset{(0.031)}{0.030}\, G_1(t^*;\eta_1,c_1) + [-\underset{(0.060)}{0.034}\,\Delta y_{t-1} - \underset{(0.050)}{0.018}\,\Delta y_{t-2} - \underset{(0.052)}{0.930}\, y_{t-1}][1 - G_2(t^*;\eta_2,c_2)] + [-\underset{(0.073)}{0.211}\,\Delta y_{t-1} - \underset{(0.058)}{0.120}\,\Delta y_{t-2}$$

$$-\underset{(0.054)}{0.326}\, y_{t-1}]G_2(t^*;\eta_2,c_2) + \underset{(0.016)}{0.080}\, G_3(t^*;\eta_3,c_3) + \underset{(0.008)}{0.005}\, D_{1t} - \underset{(0.011)}{0.076}\, D_{2t} - \underset{(0.012)}{0.120}\, D_{3t} - \underset{(0.011)}{0.076}\, D_{4t} - \underset{(0.008)}{0.046}\, D_{5t} + \underset{(0.009)}{0.016}\, D_{6t} + \underset{(0.009)}{0.080}\, D_{7t}$$

$$-\underset{(0.014)}{0.103}\, D_{8t} + \underset{(0.010)}{0.055}\, D_{9t} - \underset{(0.009)}{0.006}\, D_{10t} - \underset{(0.008)}{0.034}\, D_{11t} + \hat{\varepsilon}_t; \quad G_1(t^*;\eta_1,c_1) = [1 + \exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.001)}{0.623})/\hat{\sigma}^2_{t^*}\}]^{-1};$$

$$G_2(t^*;\eta_2,c_2) = [1 + \exp\{-\exp(\underset{(0.398)}{1.705})(t^* - \underset{(0.025)}{0.583})/\hat{\sigma}^2_{t^*}\}]^{-1}; \quad G_3(t^*;\eta_3,c_3) = [1 + \exp\{-\exp(\underset{(0.657)}{3.060})(t^* - \underset{(0.017)}{0.077})/\hat{\sigma}^2_{t^*}\}]^{-1}.$$

$R^2 = 0.501$, $\hat{\sigma}_{NL} = 0.0872$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.938$, AIC $= -1.970$, SBC $= -1.681$, LJB $= 2.289\,(0.318)$, $\mathrm{LM}_{SC}(4) = 0.511\,(0.728)$, $\mathrm{LM}_{ARCH}(4) = 3.781\,(5.0510^{-5})$,
$\mathrm{LM}_{SC}(12) = 0.365\,(0.975)$, $\mathrm{LM}_{ARCH}(12) = 1.850\,(0.040)$, $\mathrm{LM}_C(Int) = 0.609\,(0.609)$, $\mathrm{LM}_C(AR) = 0.418\,(0.956)$, $\mathrm{LM}_C(Seas) = 1.013\,(0.452)$.

Panel B, $y_t = ln(NYC_t/CVG_t)$

$$\Delta y_t = [-\underset{(0.080)}{0.152}\,\Delta y_{t-1} - \underset{(0.060)}{0.037}\,\Delta y_{t-2} - \underset{(0.081)}{0.697}\, y_{t-1}][1 - G_1(t^*;\eta_1,c_1)] + [-\underset{(0.055)}{0.166}\,\Delta y_{t-1} - \underset{(0.042)}{0.168}\,\Delta y_{t-2} - \underset{(0.056)}{0.484}\, y_{t-1}]G_1(t^*;\eta_1,c_1) + [\underset{(0.024)}{0.198} + \underset{(0.014)}{0.025}\, D_{1t}$$

$$-\underset{(0.020)}{0.095}\, D_{2t} - \underset{(0.023)}{0.008}\, D_{3t} - \underset{(0.016)}{0.066}\, D_{4t} - \underset{(0.015)}{0.060}\, D_{5t} - \underset{(0.020)}{0.046}\, D_{6t} + \underset{(0.019)}{0.087}\, D_{7t} + \underset{(0.018)}{0.220}\, D_{8t} - \underset{(0.022)}{0.021}\, D_{9t} + \underset{(0.016)}{0.016}\, D_{10t} - \underset{(0.018)}{0.041}\, D_{11t}][1 - G_2(t^*;\eta_2,c_2)]$$

$$+[\underset{(0.020)}{0.148} - \underset{(0.017)}{0.044}\, D_{1t} - \underset{(0.034)}{0.020}\, D_{2t} + \underset{(0.014)}{0.036}\, D_{3t} - \underset{(0.015)}{0.079}\, D_{4t} - \underset{(0.015)}{0.052}\, D_{5t} + \underset{(0.014)}{0.009}\, D_{6t} + \underset{(0.015)}{0.056}\, D_{7t} + \underset{(0.011)}{0.146}\, D_{8t} - \underset{(0.015)}{0.052}\, D_{9t} + \underset{(0.014)}{0.032}\, D_{10t}$$

$$-\underset{(0.016)}{0.041}\, D_{11t}]G_2(t^*;\eta_2,c_2) + \hat{\varepsilon}_t; \quad G_1(t^*;\eta_1,c_1) = [1 + \exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.002)}{0.656})/\hat{\sigma}^2_{t^*}\}]^{-1}; \quad G_2(t^*;\eta_2,c_2) = [1 + \exp\{-\exp(\underset{(0.519)}{4.068})(t^* - \underset{(0.009)}{0.599})^2/\hat{\sigma}^2_{t^*}\}]^{-1}.$$

$R^2 = 0.646$, $\hat{\sigma}_{NL} = 0.0830$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.955$, AIC $= -2.047$, SBC $= -1.670$, LJB $= 90.647\,(2.0710^{-20})$, $\mathrm{LM}_{SC}(4) = 0.597\,(0.665)$, $\mathrm{LM}_{ARCH}(4) = 1.925\,(0.106)$,
$\mathrm{LM}_{SC}(12) = 0.501\,(0.903)$, $\mathrm{LM}_{ARCH}(12) = 1.024\,(0.426)$, $\mathrm{LM}_C(Int) = 1.051\,(0.370)$, $\mathrm{LM}_C(AR) = 1.373\,(0.177)$, $\mathrm{LM}_C(Seas) = 1.698\,(0.012)$.

Panel C, $y_t = ln(NYC_t/DBQ_t)$

$$\Delta y_t = [\underset{(0.026)}{0.254} + \underset{(0.074)}{0.106}\,\Delta y_{t-1} - \underset{(0.086)}{0.896}\, y_{t-1}][1 - G_1(t^*;\eta_1,c_1)] + [\underset{(0.028)}{0.221} - \underset{(0.068)}{0.100}\,\Delta y_{t-1} - \underset{(0.071)}{0.585}\, y_{t-1}]G_1(t^*;\eta_1,c_1,c_2) - \underset{(0.019)}{0.027}\, D_{1t} - \underset{(0.016)}{0.141}\, D_{2t} - \underset{(0.020)}{0.187}\, D_{3t}$$

$$-\underset{(0.021)}{0.014}\, D_{4t} - \underset{(0.021)}{0.012}\, D_{5t} + \underset{(0.017)}{0.031}\, D_{6t} + \underset{(0.018)}{0.060}\, D_{7t} + \underset{(0.017)}{0.079}\, D_{8t} + \underset{(0.017)}{0.109}\, D_{9t} + \underset{(0.020)}{0.016}\, D_{10t} + \underset{(0.019)}{0.044}\, D_{11t} + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1,c_1) = [1 + \exp\{-\exp(\underset{(1.202)}{2.614})(t^* - \underset{(0.029)}{0.454})/\hat{\sigma}^2_{t^*}\}]^{-1}.$$

$R^2 = 0.510$, $\hat{\sigma}_{NL} = 0.1187$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.963$, AIC $= -1.447$, SBC $= -1.236$, LJB $= 2.218\,(0.329)$, $\mathrm{LM}_{SC}(4) = 0.205\,(0.936)$, $\mathrm{LM}_{ARCH}(4) = 1.181\,(0.319)$,
$\mathrm{LM}_{SC}(12) = 0.563\,(0.871)$, $\mathrm{LM}_{ARCH}(12) = 1.980\,(0.025)$, $\mathrm{LM}_C(Int) = 1.492\,(0.216)$, $\mathrm{LM}_C(AR) = 1.676\,(0.094)$, $\mathrm{LM}_C(Seas) = 1.532\,(0.035)$.

Table 4: Continued.

Panel D, $y_t = ln(NYC_t/MSP_t)$

$$\Delta y_t = [\underset{(0.030)}{0.212} + \underset{(0.113)}{0.026}\,\Delta y_{t-1} + \underset{(0.089)}{0.027}\,\Delta y_{t-2} - \underset{(0.131)}{0.967}\,y_{t-1}][1 - G_1(t^*;\eta_1,c_1)] + [\underset{(0.028)}{0.199} - \underset{(0.071)}{0.209}\,\Delta y_{t-1} - \underset{(0.064)}{0.063}\,\Delta y_{t-2} - \underset{(0.075)}{0.541}\,y_{t-1}]G_1(t^*;\eta_1,c_1) - \underset{(0.018)}{0.025}\,D_{1t}$$

$$- \underset{(0.013)}{0.084}\,D_{2t} - \underset{(0.019)}{0.142}\,D_{3t} - \underset{(0.018)}{0.070}\,D_{4t} - \underset{(0.017)}{0.016}\,D_{5t} + \underset{(0.016)}{0.040}\,D_{6t} + \underset{(0.015)}{0.068}\,D_{7t} + \underset{(0.017)}{0.050}\,D_{8t} + \underset{(0.015)}{0.080}\,D_{9t} + \underset{(0.015)}{0.037}\,D_{10t} + \underset{(0.019)}{0.011}\,D_{11t} + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1,c_1) \;=\; [1 + \exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.004)}{0.436})/\hat{\sigma}^2_{t^*}\}]^{-1}.$$

$R^2 = 0.477$, $\hat{\sigma}_{NL} = 0.1118$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.953$, AIC $= -1.480$, SBC $= -1.227$, LJB $= 170.62\,(8.8910^{-38})$, $\mathrm{LM}_{SC}(4) = 1.002\,(0.407)$, $\mathrm{LM}_{ARCH}(4) = 0.658\,(0.622)$, $\mathrm{LM}_{SC}(12) = 0.683\,(0.767)$, $\mathrm{LM}_{ARCH}(12) = 0.331\,(0.983)$, $\mathrm{LM}_C(Int) = 2.180\,(0.090)$, $\mathrm{LM}_C(AR) = 1.233\,(0.259)$, $\mathrm{LM}_C(Seas) = 1.325\,(0.117)$.

Panel E, $y_t = ln(NYC_t/STL_t)$

$$\Delta y_t = [\underset{(0.093)}{0.343} - \underset{(0.128)}{0.237}\,\Delta y_{t-1} - \underset{(0.070)}{0.051}\,\Delta y_{t-2} - \underset{(0.248)}{0.880}\,y_{t-1} + \underset{(0.023)}{0.012}\,D_{1t} - \underset{(0.033)}{0.083}\,D_{2t} - \underset{(0.022)}{0.153}\,D_{3t} - \underset{(0.034)}{0.096}\,D_{4t} - \underset{(0.025)}{0.027}\,D_{5t} + \underset{(0.030)}{0.001}\,D_{6t} + \underset{(0.022)}{0.137}\,D_{7t} + \underset{(0.072)}{0.331}\,D_{8t}$$

$$+ \underset{(0.038)}{0.021}\,D_{9t} - \underset{(0.035)}{0.054}\,D_{10t} - \underset{(0.030)}{0.027}\,D_{11t}][1 - G_1(t^*;\eta_1,c_1)] + [\underset{(0.082)}{0.105} - \underset{(0.147)}{0.210}\,\Delta y_{t-1} - \underset{(0.138)}{0.235}\,\Delta y_{t-2} - \underset{(0.213)}{0.225}\,y_{t-1} - \underset{(0.058)}{0.042}\,D_{1t} - \underset{(0.075)}{0.140}\,D_{2t} - \underset{(0.066)}{0.095}\,D_{3t}$$

$$- \underset{(0.046)}{0.076}\,D_{4t} - \underset{(0.032)}{0.065}\,D_{5t} + \underset{(0.043)}{0.068}\,D_{6t} + \underset{(0.036)}{0.131}\,D_{7t} + \underset{(0.092)}{0.040}\,D_{8t} + \underset{(0.041)}{0.018}\,D_{9t} + \underset{(0.052)}{0.005}\,D_{10t} + \underset{(0.065)}{0.090}\,D_{11t}]G_1(t^*;\eta_1,c_1) + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1,c_1) \;=\; [1 + \exp\{-\exp(\underset{(0.499)}{0.563})(t^* - \underset{(0.203)}{0.653})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.651$, $\hat{\sigma}_{NL} = 0.1051$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.945$, AIC $= -1.694$, SBC $= -1.339$, LJB $= 13.841\,(9.8710^{-4})$, $\mathrm{LM}_{SC}(4) = 0.541\,(0.705)$, $\mathrm{LM}_{ARCH}(4) = 0.811\,(0.519)$, $\mathrm{LM}_{SC}(12) = 0.723\,(0.729)$, $\mathrm{LM}_{ARCH}(12) = 0.976\,(0.471)$, $\mathrm{LM}_C(Int) = 1.631\,(0.182)$, $\mathrm{LM}_C(AR) = 0.759\,(0.692)$, $\mathrm{LM}_C(Seas) = 1.108\,(0.318)$.

Panel F, $y_t = ln(CHI_t/BWI_t)$

$$\Delta y_t = [-\underset{(0.066)}{0.144}\,\Delta y_{t-1} - \underset{(0.065)}{0.611}\,y_{t-1}][1 - G_1(t^*;\eta_1,c_1)] + [-\underset{(0.007)}{0.031}\,\Delta y_{t-1} - \underset{(0.077)}{0.238}\,y_{t-1}]G_1(t^*;\eta_1,c_1) + [-\underset{(0.011)}{0.082} - \underset{(0.020)}{0.042}\,D_{1t} + \underset{(0.014)}{0.048}\,D_{2t} + \underset{(0.027)}{0.084}\,D_{3t}$$

$$- \underset{(0.019)}{0.040}\,D_{4t} + \underset{(0.016)}{0.071}\,D_{5t} - \underset{(0.012)}{0.084}\,D_{6t} - \underset{(0.030)}{0.066}\,D_{7t} + \underset{(0.014)}{0.089}\,D_{8t} - \underset{(0.018)}{0.036}\,D_{9t} + \underset{(0.016)}{0.008}\,D_{10t} - \underset{(0.013)}{0.046}\,D_{11t}][1 - G_2(t^*;\eta_2,c_2)] + [-\underset{(0.007)}{0.031} + \underset{(0.016)}{0.038}\,D_{1t}$$

$$+ \underset{(0.018)}{0.045}\,D_{2t} + \underset{(0.021)}{0.045}\,D_{3t} + \underset{(0.016)}{0.049}\,D_{4t} + \underset{(0.013)}{0.004}\,D_{5t} - \underset{(0.015)}{0.042}\,D_{6t} - \underset{(0.016)}{0.067}\,D_{7t} + \underset{(0.018)}{0.023}\,D_{8t} - \underset{(0.014)}{0.096}\,D_{9t} + \underset{(0.017)}{0.017}\,D_{10t} - \underset{(0.016)}{0.009}\,D_{11t}]G_2(t^*;\eta_2,c_2) + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1,c_1) \;=\; [1 + \exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.003)}{0.591})/\hat{\sigma}_{t^*}\}]^{-1}; \;\; G_2(t^*;\eta_2,c_2) \;=\; 1 - \exp\{-\exp(\underset{(0.639)}{1.330})(t^* - \underset{(0.024)}{0.265})^8/\hat{\sigma}^8_{t^*}\}.$$

$R^2 = 0.541$, $\hat{\sigma}_{NL} = 0.0836$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.956$, AIC $= -2.036$, SBC $= -1.687$, LJB $= 8.978\,(0.011)$, $\mathrm{LM}_{SC}(4) = 0.533\,(0.711)$, $\mathrm{LM}_{ARCH}(4) = 0.452\,(0.771)$, $\mathrm{LM}_{SC}(12) = 1.223\,(0.266)$, $\mathrm{LM}_{ARCH}(12) = 0.728\,(0.724)$, $\mathrm{LM}_C(Int) = 2.653\,(0.049)$, $\mathrm{LM}_C(AR) = 1.433\,(0.173)$, $\mathrm{LM}_C(Seas) = 1.276\,(0.149)$.

Table 4: Continued.

Panel G, $y_t = ln(CHI_t/CVG_t)$

$$\Delta y_t = [-\underset{(0.138)}{0.070}\,\Delta y_{t-1} - \underset{(0.086)}{0.010}\,\Delta y_{t-2} - \underset{(0.181)}{0.804}\,y_{t-1}][1 - G_1(t^*;\eta_1,c_1)] + [-\underset{(0.019)}{0.229}\,\Delta y_{t-1} - \underset{(0.098)}{0.117}\,\Delta y_{t-2} - \underset{(0.050)}{0.428}\,y_{t-1}]G_1(t^*;\eta_1,c_1) + [\underset{(0.012)}{0.060} + \underset{(0.020)}{0.021}\,D_{1t} - \underset{(0.029)}{0.033}\,D_{2t}$$

$$+ \underset{(0.033)}{0.141}\,D_{3t} - \underset{(0.035)}{0.025}\,D_{4t} - \underset{(0.020)}{0.041}\,D_{5t} - \underset{(0.026)}{0.092}\,D_{6t} + \underset{(0.020)}{0.013}\,D_{7t} + \underset{(0.019)}{0.119}\,D_{8t} - \underset{(0.020)}{0.054}\,D_{9t} + \underset{(0.017)}{0.009}\,D_{10t} - \underset{(0.017)}{0.046}\,D_{11t}][1 - G_2(t^*;\eta_2,c_2)] + [-\underset{(0.008)}{0.002} - \underset{(0.017)}{0.033}\,D_{1t}$$

$$+ \underset{(0.035)}{0.067}\,D_{2t} + \underset{(0.033)}{0.106}\,D_{3t} + \underset{(0.014)}{0.028}\,D_{4t} + \underset{(0.021)}{0.006}\,D_{5t} + \underset{(0.023)}{0.014}\,D_{6t} - \underset{(0.019)}{0.030}\,D_{7t} + \underset{(0.028)}{0.048}\,D_{8t} - \underset{(0.018)}{0.124}\,D_{9t} + \underset{(0.023)}{0.022}\,D_{10t} - \underset{(0.042)}{0.076}\,D_{11t}]G_2(t^*;\eta_2,c_2) + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1,c_1) \;=\; [1+\exp\{-\exp(\underset{(0.929)}{1.781})(t^* - \underset{(0.065)}{0.380})/\hat{\sigma}^2_{t^*}\}]^{-1};\;\; G_2(t^*;\eta_2,c_2) \;=\; [1+\exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.004)}{0.583})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.572$, $\hat{\sigma}_{NL} = 0.1098$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.947$, AIC $= -1.596$, SBC $= -1.219$, LJB $= 140.53\,(3.0610^{-31})$, $\text{LM}_{SC}(4) = 0.913\,(0.456)$, $\text{LM}_{ARCH}(4) = 0.652\,(0.626)$, $\text{LM}_{SC}(12) = 1.107\,(0.354)$, $\text{LM}_{ARCH}(12) = 0.777\,(0.674)$, $\text{LM}_C(Int) = 0.895\,(0.444)$, $\text{LM}_C(AR) = 1.374\,(0.177)$, $\text{LM}_C(Seas) = 0.890\,(0.645)$.

Panel H, $y_t = ln(CHI_t/MSP_t)$

$$\Delta y_t = \underset{(0.012)}{0.038}[1 - G_1(t^*;\eta_1,c_1)] + \underset{(0.006)}{0.023}\,G_1(t^*;\eta_1,c_1) + [\underset{(0.101)}{0.017}\,\Delta y_{t-1} - \underset{(0.122)}{1.029}\,y_{t-1} - \underset{(0.044)}{0.077}\,D_{1t} - \underset{(0.024)}{0.001}\,D_{2t} - \underset{(0.040)}{0.120}\,D_{3t} - \underset{(0.041)}{0.034}\,D_{4t} + \underset{(0.023)}{0.079}\,D_{5t} + \underset{(0.014)}{0.052}\,D_{6t}$$

$$+ \underset{(0.021)}{0.005}\,D_{7t} - \underset{(0.015)}{0.082}\,D_{8t} + \underset{(0.039)}{0.055}\,D_{9t} + \underset{(0.017)}{0.056}\,D_{10t} - \underset{(0.016)}{0.022}\,D_{11t}][1 - G_2(t^*;\eta_2,c_2)] + [-\underset{(0.046)}{0.192}\,\Delta y_{t-1} - \underset{(0.048)}{0.387}\,y_{t-1} - \underset{(0.011)}{0.010}\,D_{1t} - \underset{(0.014)}{0.012}\,D_{2t} + \underset{(0.022)}{0.019}\,D_{3t}$$

$$+ \underset{(0.016)}{0.011}\,D_{4t} + \underset{(0.011)}{0.019}\,D_{5t} + \underset{(0.008)}{0.025}\,D_{6t} - \underset{(0.009)}{0.020}\,D_{7t} - \underset{(0.011)}{0.050}\,D_{8t} + \underset{(0.016)}{0.030}\,D_{9t} + \underset{(0.010)}{0.018}\,D_{10t} - \underset{(0.010)}{0.035}\,D_{11t}]G_2(t^*;\eta_2,c_2) + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1,c_1) \;=\; [1+\exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.002)}{0.308})/\hat{\sigma}^2_{t^*}\}]^{-1};\;\; G_2(t^*;\eta_2,c_2) \;=\; 1-\exp\{-\exp(\underset{(-)}{5.011})(t^* - \underset{(0.016)}{0.282})^8/\hat{\sigma}^8_{t^*}\}.$$

$R^2 = 0.460$, $\hat{\sigma}_{NL} = 0.1061$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.965$, AIC $= -1.619$, SBC $= -1.241$, LJB $= 27.14\,(1.2810^{-6})$, $\text{LM}_{SC}(4) = 0.798\,(0.528)$, $\text{LM}_{ARCH}(4) = 1.514\,(0.198)$, $\text{LM}_{SC}(12) = 0.621\,(0.823)$, $\text{LM}_{ARCH}(12) = 1.397\,(0.166)$, $\text{LM}_C(Int) = 1.346\,(0.260)$, $\text{LM}_C(AR) = 1.011\,(0.431)$, $\text{LM}_C(Seas) = 1.806\,(0.006)$.

Table 4: Continued.

Panel G, $y_t = ln(CHI_t/STL_t)$

$$\Delta y_t = [\underset{(0.025)}{0.156} - \underset{(0.049)}{0.195}\, \Delta y_{t-1} - \underset{(0.051)}{0.091}\, \Delta y_{t-2} - \underset{(0.141)}{0.932}\, y_{t-1} - \underset{(0.025)}{0.024}\, D_{1t} - \underset{(0.025)}{0.032}\, D_{2t} + \underset{(0.023)}{0.006}\, D_{3t} - \underset{(0.023)}{0.038}\, D_{4t} - \underset{(0.025)}{0.003}\, D_{5t} - \underset{(0.025)}{0.036}\, D_{6t} + \underset{(0.024)}{0.071}\, D_{7t} + \underset{(0.025)}{0.214}\, D_{8t}$$

$$- \underset{(0.028)}{0.012}\, D_{9t} - \underset{(0.031)}{0.049}\, D_{10t} - \underset{(0.028)}{0.038}\, D_{11t}][1 - G_1(t^*;\eta_1, c_1)] + [\underset{(0.011)}{0.027} - \underset{(0.085)}{0.228}\, \Delta y_{t-1} - \underset{(0.076)}{0.056}\, \Delta y_{t-2} - \underset{(0.078)}{0.307}\, y_{t-1} - \underset{(0.022)}{0.002}\, D_{1t} - \underset{(0.023)}{0.025}\, D_{2t} - \underset{(0.023)}{0.010}\, D_{3t}$$

$$+ \underset{(0.023)}{0.037}\, D_{4t} - \underset{(0.023)}{0.001}\, D_{5t} + \underset{(0.021)}{0.040}\, D_{6t} + \underset{(0.019)}{0.020}\, D_{7t} - \underset{(0.023)}{0.001}\, D_{8t} - \underset{(0.020)}{0.068}\, D_{9t} - \underset{(0.025)}{0.008}\, D_{10t} + \underset{(0.022)}{0.025}\, D_{11t}]G_1(t^*;\eta_1, c_1) + \hat{\varepsilon}_t;$$

$$G_1(t^*;\eta_1, c_1) \;=\; [1 + \exp\{-\exp(\underset{(0.559)}{2.047})(t^* - \underset{(0.034)}{0.519})/\hat{\sigma}_{t^*}\}]^{-1}.$$

$R^2 = 0.573$, $\hat{\sigma}_{NL} = 0.0926$, $\hat{\sigma}_{NL}/\hat{\sigma}_L = 0.919$, AIC $= -1.833$, SBC $= -1.478$, LJB $= 27.69\,(9.7110^{-7})$, $\text{LM}_{SC}(4) = 0.915\,(0.416)$, $\text{LM}_{ARCH}(4) = 0.538\,(0.708)$, $\text{LM}_{SC}(12) = 0.973\,(0.474)$, $\text{LM}_{ARCH}(12) = 1.578\,(0.097)$, $\text{LM}_C(Int) = 1.858\,(0.137)$, $\text{LM}_C(AR) = 1.179\,(0.297)$, $\text{LM}_C(Seas) = 1.154\,(0.264)$.

Note: Asymptotic standard errors are given below parameter estimates in parentheses; R^2 is the unadjusted R^2; $\hat{\varepsilon}_t$ denotes the model's residual at time t; $\hat{\sigma}_{NL}$ denotes the TVAR model's residual standard error; $\widehat{\sigma}_{NL}/\widehat{\sigma}_L$ is the ratio of the TVAR model versus AR model residual standard error; and AIC is Akaike information criterion and SBC denotes Schwarz's Bayesian Criterion. As well, LJB is the Lomnicki–Jarque–Bera test of normality of residuals, with asymptotic p–values in parentheses. $\text{LM}_{SC}(j)$ denotes the F variant of Eitrheim and Teräsvirta's (1996) LM test of no remaining autocorrelation based on j, $j = 4, 12$ lags. Likewise, $\text{LM}_{ARCH}(j)$ denotes an LM test for ARCH–type heteroskedasticity based on j, $j = 4, 12$ lags. As well, $\text{LM}_C(Int)$, $\text{LM}_C(AR)$, and $\text{LM}_C(Seas)$ are the F variants of Lim and Teräsvirta's (1994) LM test for parameter constancy in, respectively, the model's intercept, autoregressive terms, and seasonal terms. p–values are in parentheses next to test statistics.

Table 5: Select Structural Dates for Each Regional Egg Price TVAR Model's Autoregressive Structure, Select City Pairs .

City Pair	$\hat{\gamma}$	$\hat{c}$	10%	Centre	90%
New York – Chicago:[a]	5.50	0.583	1885.09	1897.03	1908.10
New York – Cincinnati:[a]	150	0.656	1892.01	1893.06	1894.10
New York – Dubuque:[a]	13.65	0.454	1894.08	1895.12	1897.04
New York – Minneapolis:[a]	150	0.436	1893.12	1894.02	1894.03
New York – St. Louis:[a]	1.76	0.653	1891.03	1901.08	1912.03
Average:			1891.07	1896.06	1901.06
Chicago – Baltimore:[a]	150	0.591	1899.09	1899.11	1900.01
Chicago – Cincinnati:[a]	150	0.599	1899.12	1900.02	1900.03
Chicago – Minneapolis:[b]	150	0.282	1887.02	1890.01	1894.07
Chicago – St. Louis:[a]	7.75	0.519	1895.06	1897.10	1908.10
Average:			1895.07	1896.06	1900.06

[a] The relevant transition function is a logistic function ($k = 1$), so that 10% (90%) denotes the dates for which the transition function is associated with a value of 0.10 (0.90), implying that 10% (90%) of the structural change adjustment has occurred. The column headed Centre denotes the date for which $t^* = \hat{c}$ for the relevant logistic function.

[b] The relevant transition function is a (symmetric) generalized exponential. As such, the data for 10% (90%) denotes the date when the transition function first (last) equals 0.10 (0.90). In this case the column headed Centre denotes the point where the transition function is at a minimum.

Note: $\hat{\gamma}$ is the estimated speed–of–adjustment parameter for the relevant transition function, while $\hat{c}$ is the corresponding estimate of the centrality parameter.

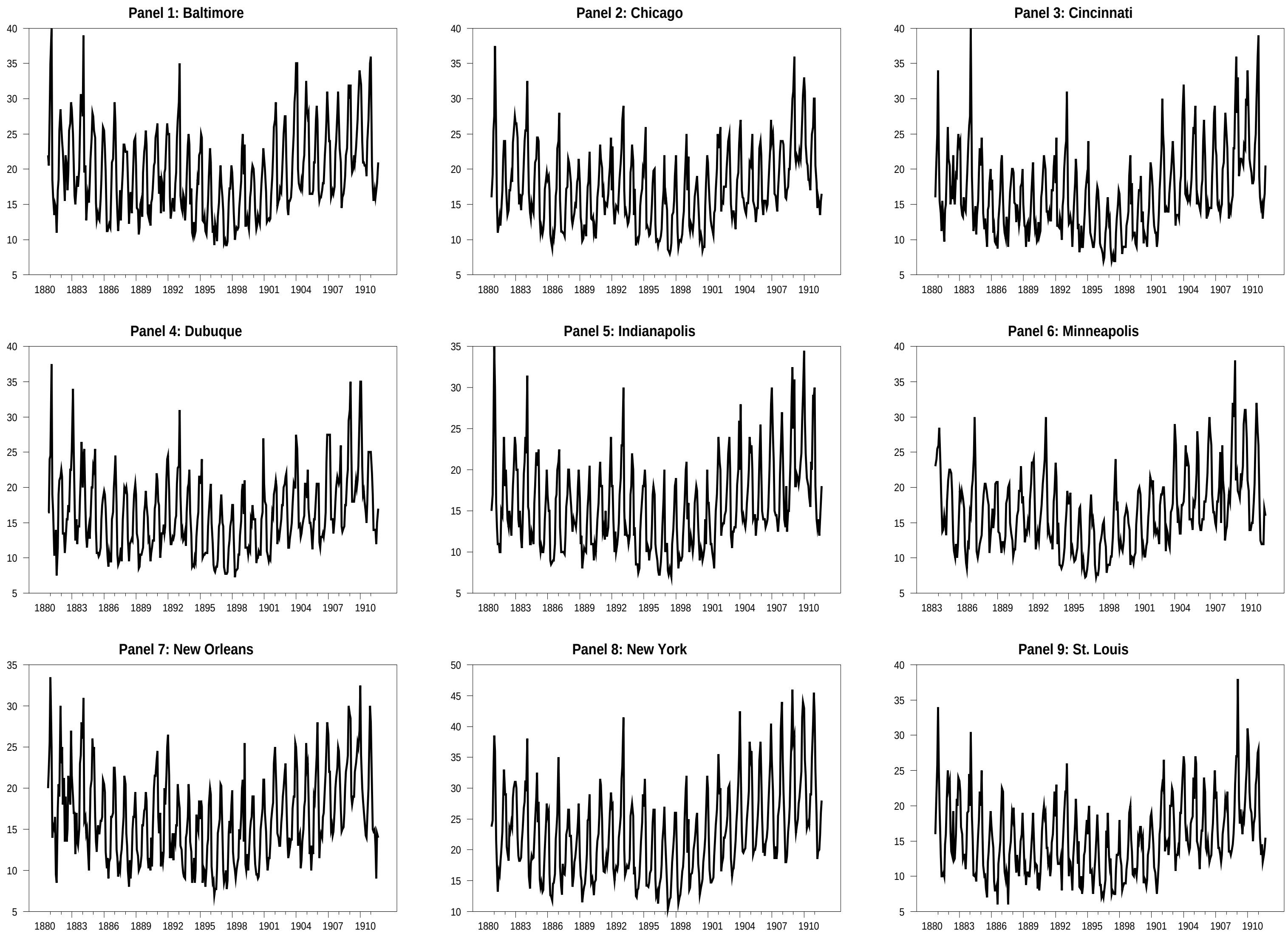

Figure 1: Regional Egg Price Data, cents/dozen, 1880–1911.

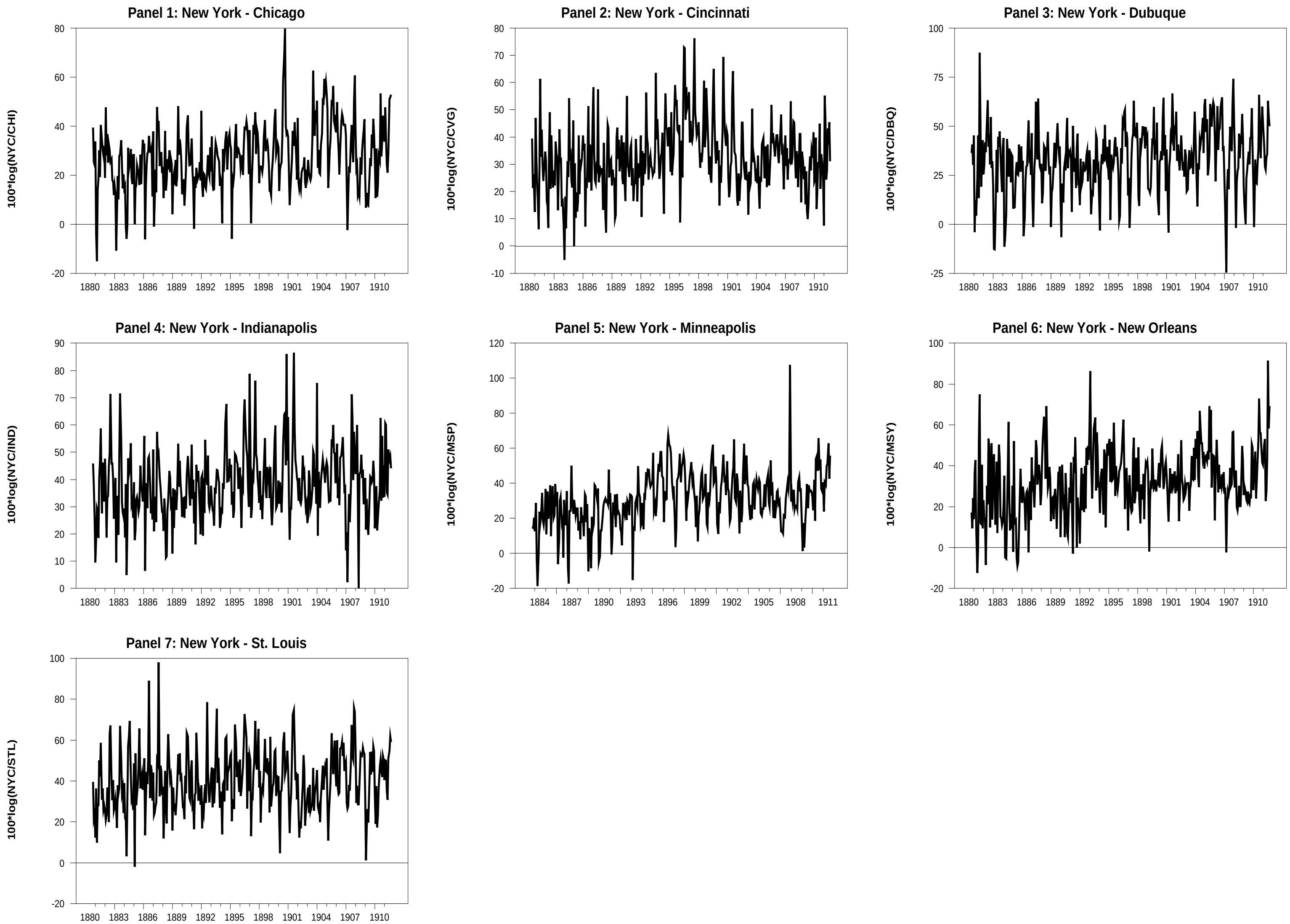

Figure 2: Log Relative Price Pairs with New York as the Central Market, 1880–1911.

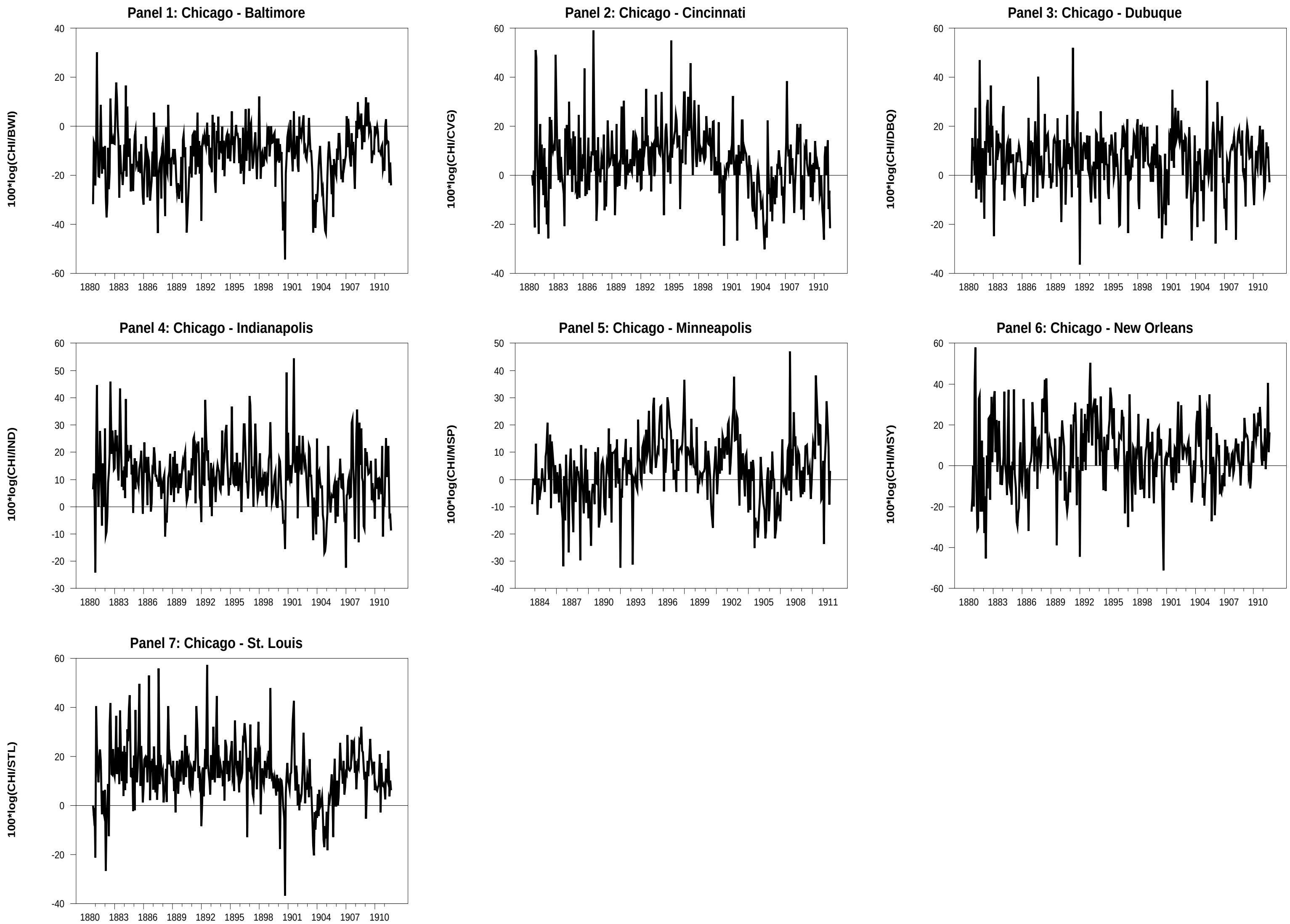

Figure 3: Log Relative Price Pairs with Chicago as the Central Market, 1880–1911.

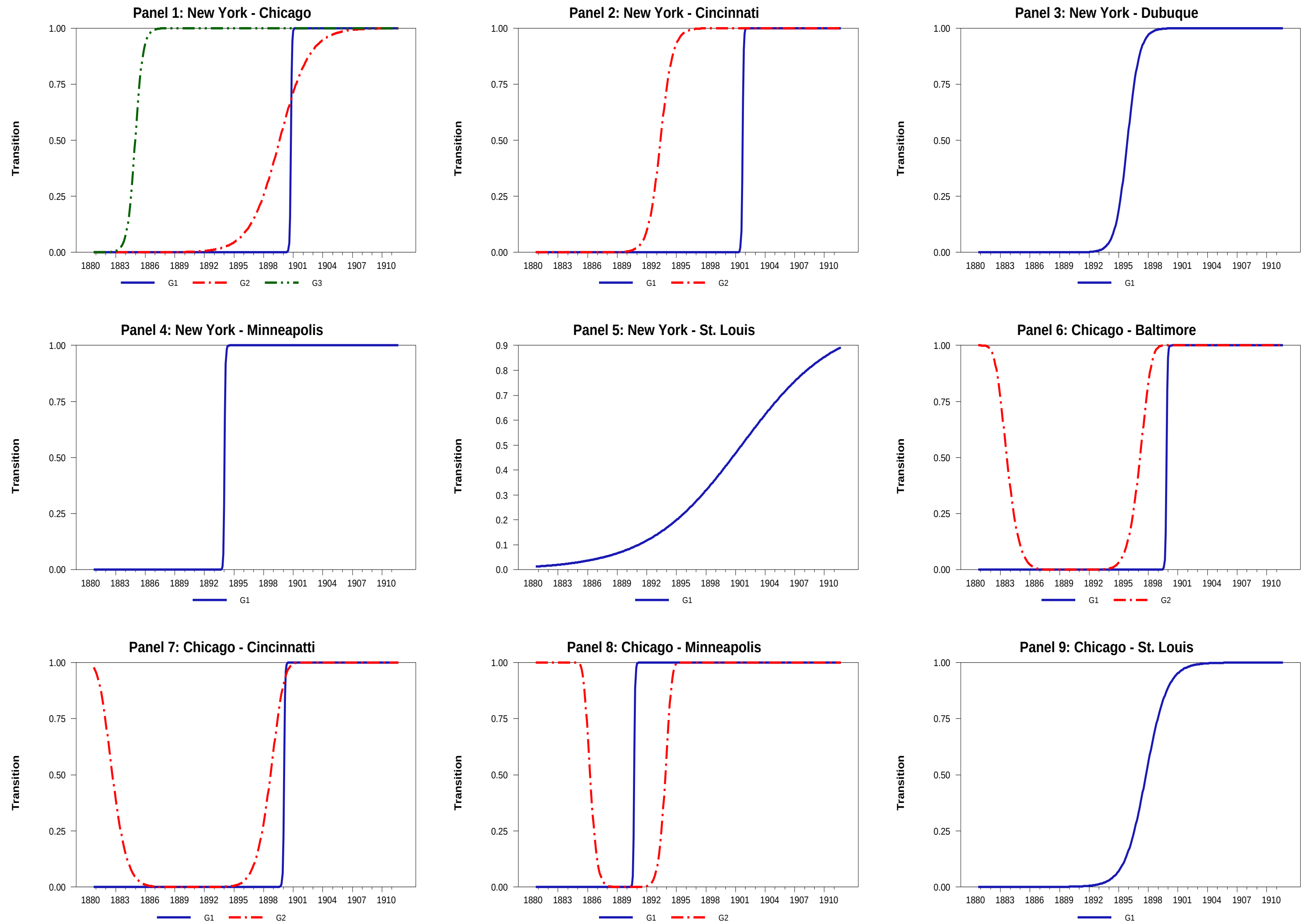

Figure 4: Estimated Transition Functions for TVAR Models of Relative Egg Prices, Select City Pairs, 1880–1911. The solid line denotes the first transition function, $G_1(.)$; the dash–dot line the second transition function, $G_2(.)$; and the dash–dot–dot line the third transition function, $G_3(.)$.

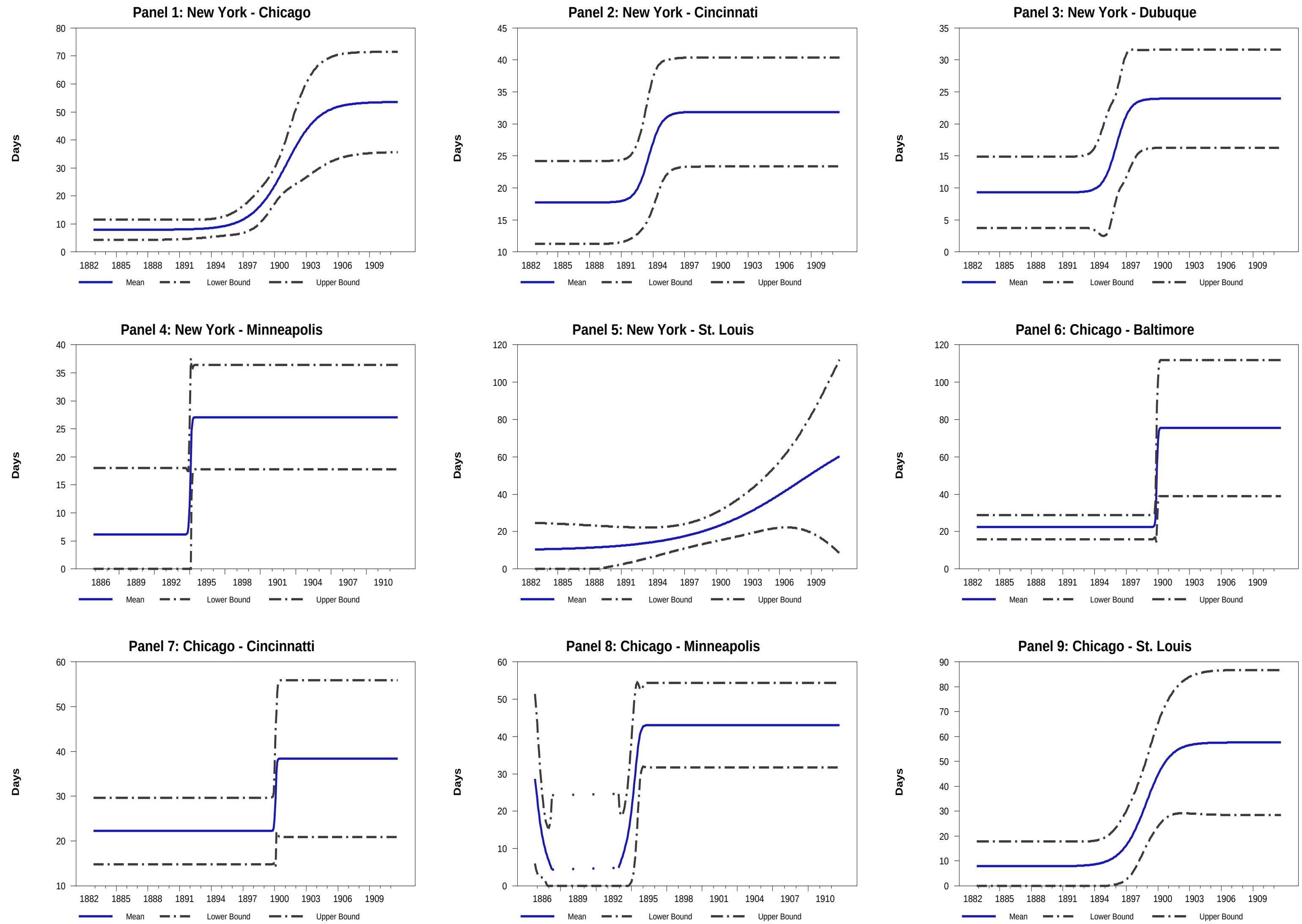

Figure 5: Estimated Mean Half Life Paths (solid line) and 90–percent Confidence Bands (dashed lines) for Estimated TVAR Models of Relative Egg Prices, Select City Pairs, 1882–1911.