TO POOL OR NOT TO POOL: HOMOGENEOUS VERSUS HETEROGENEOUS ESTIMATORS APPLIED TO CIGARETTE DEMAND

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Abstract—This paper reexamines the benefits of pooling and, in addition, contrasts the performance of newly proposed heterogeneous estimators. The analysis utilizes a panel data set from 46 American states over the period 1963 to 1992 and a dynamic demand specification for cigarettes. Also, the forecast performance of the various estimators is compared.

I. Introduction

There has been a recent proliferation of pooled and heterogeneous estimators with the latter questioning the benefits of pooling. We place this debate within the context of cigarette demand because of the policy importance of the long-run price elasticity of demand in affecting tax revenues and discouraging consumption. Both from a methodological as well as a policy perspective, the long-run price elasticity of cigarette demand remains an important unresolved issue. An interesting methodological question is to what degree can elasticity differences be attributable to the manner in which applied econometricians analyze a given body of data. Specifically, this study standardizes on the frequently utilized dynamic demand specification and a common data set (annual data for 46 states covering the period 1963–1992) and asks the following three questions.

(1) How do the price elasticity estimates differ depending on the estimation approach?
(2) Based on predictive performance, which estimates are more plausible?
(3) Do these findings suggest useful rules of thumb to applied researchers facing the decision to pool or not to pool?

Armed with a panel data set, the researcher faces a wide variety of estimation options. For example, if heterogeneity between states is viewed as pervasive, one can simply forsake pooling and apply individual time series to each state. Alternatively, if one believes that the long-run response is best captured by cross-sectional variation, a between state regression approach can be employed. The Baltagi and Levin (1986) cigarette-demand study argues persuasively for pooling the data as the best approach for obtaining reliable price and income elasticities. It also points out that pure cross-section studies cannot control for state-specific effects, whereas pure time-series studies cannot control for unobservable taste changes occurring over time. But, even if one agrees that a pooled estimator is preferable to individual time-series or cross-section estimates, there remains the question of which pooled estimators yields the most plausible estimates.

More recently, the fundamental homogeneity assumption underlying pooled models has been called into question. Robertson and Symons (1992), Pesaran and Smith (1995) and Maddala et al. (1994) argue in favor of heterogeneous estimates rather than the traditional homogeneous estimates. Depending on the extent of interstate heterogeneity in parameters, researchers may prefer these heterogeneous estimators to the traditional pooled homogeneous parameter estimators.

Our objective in this study is to compare the performance of both these homogeneous and heterogeneous estimators applying them to a well-researched good (cigarette consumption), a common data set (a panel of 46 states), and a routinely applied dynamic demand specification. In comparing pooled homogeneous estimators and their heterogeneous rivals, we examine the plausibility of alternative estimates of the price and income elasticities as well as the speed of the adjustment path to long-run equilibrium. Admittedly, ours is a ‘‘case study’’ for cigarette demand. The fact that these findings corroborate similar results using an international panel for gasoline consumption (Baltagi and Griffin (1997)) suggests that the findings offer useful general guidelines to applied researchers facing the dilemma ‘‘to pool or not to pool.’’

A distinctive characteristic of this paper is that we compare the forecast performance of these alternative approaches using the model to provide forecasts of cigarette consumption over a ten-year horizon. Section II briefly reviews the standard habit-persistence type of dynamic demand specification. Section III presents the pooled homogeneous parameter results, while section IV presents the heterogeneous model results. Section V compares the plausibility of the various estimates and their forecasting performance over horizons of one, five, and ten years. Section VI recapitulates our major findings.

II. Model Specification

Following Laughhunn and Lyon (1971), Hamilton (1972), Doron (1979), and Baltagi and Levin (1986), it is reasonable to model cigarette demand as follows.

$$C_{it} = f(P_{it}, Y_{it}, Pn_{it}, Z_i, Z_t), \qquad (1)$$

where C_{it} is real per capita sales of cigarettes (measured in packs of cigarettes per head) by persons of smoking age (sixteen years and older), P_{it} is the average retail price of a pack of cigarettes measured in real terms, Y_{it} is real per

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capita disposable income, and Pn_{it} denotes the minimum real price of cigarettes in any neighboring state.[1] This enables controlling for possible "bootlegging effects," which Baltagi and Levin (1986) found important in explaining why some very low tax states enjoy much higher cigarette sales than neighboring states with higher taxes.[2] The subscript i denotes the i_{th} state ($i = 1, \ldots, 46$), and the subscript t denotes the t_{th} year ($t = 1, \ldots, 30$). This study updates the original Baltagi and Levin data twelve more years from 1981 to 1992, so that the panel covers 46 states over thirty years (1963–1992). Z_i denotes a vector of state-specific, time-invariant variables that include religion, race, education, tax-free Indian reservations, and tourism. Z_t denotes a vector of year-specific, state-invariant variables that include health warnings due to the Surgeon General, warning labels by the Federal Trade Commission, national advertising expenditures on TV and radio, and the ban of broadcast advertising of cigarettes effective January, 1971.

Following Houthakker and Taylor (1970) and McGuiness and Cowling (1975), we assume that cigarette consumption is governed by a partial adjustment or habit-persistence model; that is,

$$\ln C_{it} - \ln C_{i,t-1} = \delta(\ln C^*_{it} - \ln C_{i,t-1}) + u_{it}, \tag{2}$$

where $\ln C^*_{it}$ is the expected or desired level of consumption of cigarettes which is given by

$$\begin{aligned}\ln C^*_{it} = \alpha^* + \beta^*_1 \ln P_{it} + \beta^*_2 \ln Y_{it} + \beta^*_3 \ln Pn_{it} \\ + Z'_i\gamma^* + Z'_t\eta^*.\end{aligned} \tag{3}$$

Substituting equation (3) into (2) produces the following log-linear dynamic demand model:

$$\begin{aligned}\ln C_{it} = \alpha + (1 - \delta) \ln C_{i,t-1} + \beta_1 \ln P_{it} + \beta_2 \ln Y_{it} \\ + \beta_3 \ln Pn_{it} + Z'_i\gamma + Z'_t\eta + u_{it},\end{aligned} \tag{4}$$

where $\alpha = \delta\alpha^*$, $\beta_j = \delta\beta^*_j$ for $j = 1,2,3$, $\gamma = \delta\gamma^*$, and $\eta = \delta\eta^*$.

We follow the usual convention (Hsiao (1986)) of assuming that the disturbance term in equation (1) is specified as a two-way error component model:

$$\begin{aligned}u_{it} &= \mu_i + \lambda_t + \nu_{it} \\ i &= 1, 2, \ldots, 46; \qquad t = 1, 2, \ldots, 30\end{aligned} \tag{5}$$

where μ_i denotes a state-specific effect, λ_t denotes a year-specific effect, and ν_{it} is white noise. One of the major advantages of a panel is its ability to control for all time-invariant variables or state-invariant variables whose omission could bias the estimates in a typical cross-section or time-series study. Both effects can be assumed to be either fixed or random. We assume that the time-period effects (the λ_t's) are fixed parameters to be estimated as coefficients of time dummies (D_t) for each year in the sample. This can be justified given the numerous policy interventions as well as health warnings and Surgeon General's reports that previous studies accounted for using time-dummy variables.[3] Major policy interventions that can change λ_t include

1. the imposition of warning labels by the Federal Trade Commission effective January 1965,
2. the application of the Fairness Doctrine Act to cigarette advertising in June 1967, which subsidized antismoking messages from 1968 to 1970,
3. the Congressional ban of broadcast advertising of cigarettes effective January 1971, and
4. "clean air laws" restricting smoking in the work place, public places, and commercial flights within the U.S.[4]

Similarly, the μ_i's are state-specific effects that can represent any state-specific characteristic such as:

1. Indian reservations selling tax-exempt cigarettes,
2. tax-exempt military bases in certain states,
3. a high percentage of Mormon population (a religion that forbids smoking), and
4. a highly touristic state, such as Nevada, with a per capita consumption of twice the national average.

Econometric treatment of these types of effects can range from ignoring them altogether to incorporating a full set of state dummy variables (D_i) for $i = 1, 2, \ldots, 46$. An intermediate solution is to explicitly model these state attributes by including state-specific, time-invariant variables, which we denote by Z_i. These include religion, race, education, and a state tourism index.[5]

[1] For data sources, as well as details on the construction of the neighboring price, see Baltagi and Levin (1986). Per capita sales of cigarettes and the average retail price per pack were obtained from The Tobacco Institute (1993). Other studies indicating the importance of bootlegging include Manchester (1976) and Warner (1982).

[2] The Advisory Commission on Intergovernmental Relations estimates that, in 1975, cigarette bootlegging cost the high-tax states \$391 million. The seriousness of the problem was officially recognized by the enactment of the 1978 Federal Contraband Act which made the transportation of contraband cigarettes in interstate commerce a federal criminal offense.

[3] See Hamilton (1972) and Baltagi and Levin (1986).

[4] See Doron (1979), appendix A, for a chronology of Federal Commission interventions in the market practices of the cigarette industry. See also the 1989 Surgeon General's report (USDHHS, 1989), which finds that, in 1985, one out of every six deaths in the U.S. was the result of past and current smoking.

[5] Religion is a group of variables giving the percentage of the state's population that is Mormon, Catholic, Southern Baptist, United Methodist, United Church of Christ, Episcopalian, Jewish, and Lutheran. Race gives the percentage of the state's population that is black, white, Asian, Hispanic, Pacific Islander, or Eskimo/American Indian. Education gives the percentage of the state's population in secondary and elementary schools. The tourism variable gives the percentage of the state's revenue from tourism-related services. The religion variable is obtained from Johnson et al. (1974). The percentage of the state's population that is Jewish is obtained from the *American Jewish Yearbook.* The tourism and race variables are obtained from the *County and City Data Book.* The education variable is obtained from the *Statistical Abstract of the United States.*

TABLE 1.—CIGARETTE DEMAND: HOMOGENEOUS PARAMETER ESTIMATES 1963–1992

Model Type	Short Run				Long Run		
	$\ln C_{it-1}$	$\ln P_{it}$	$\ln Pn_{it}$	$\ln Y_{it}$	$\ln P_{it}$	$\ln Pn_{it}$	$\ln Y_{it}$
A. Traditional Pooled Estimators							
OLS	0.97	−0.090	0.024	−0.03	−2.90	0.77	−1.00
	(157.7)	(6.2)	(1.8)	(5.1)	(5.04)	(1.78)	(3.39)
OLS with D_t	0.95	−0.137	0.037	−0.01	−2.98	0.80	−0.20
	(148.5)	(8.7)	(2.7)	(1.1)	(7.76)	(2.60)	(1.06)
OLS with Z_i and D_t	0.90	−0.187	0.053	0.042	−1.95	0.55	0.44
	(102.7)	(11.1)	(3.2)	(3.3)	(11.79)	(3.08)	(3.51)
Within	0.83	−0.299	0.034	0.10	−1.79	0.20	0.60
	(66.3)	(12.7)	(1.2)	(4.2)	(12.38)	(1.22)	(4.27)
GLS with Z_i and D_t	0.91	−0.178	0.050	0.03	−2.00	0.56	0.31
	(106.4)	(10.8)	(3.1)	(2.3)	(11.16)	(3.03)	(2.46)
GLS-AR(1) with Z_i	0.96	−0.089	0.016	−0.03	−2.09	0.37	−0.63
	(147.6)	(6.8)	(1.3)	(4.0)	(6.64)	(1.32)	(3.27)
B. 2SLS Type Pooled Estimators							
2SLS	0.85	−0.205	0.052	−0.02	−1.37	0.35	−0.11
	(25.3)	(5.8)	(3.1)	(2.2)	(11.97)	(1.52)	(1.46)
2SLS with Z_i and D_t	0.63	−0.482	0.073	0.19	−1.31	0.20	0.51
	(17.3)	(11.1)	(3.3)	(7.5)	(23.92)	(3.23)	(11.85)
2SLS-KR	0.71	−0.311	0.071	−0.02	−1.07	0.24	−0.05
	(22.7)	(13.9)	(3.7)	(1.5)	(11.80)	(3.19)	(1.55)
2SLS-KR with Z_i	0.61	−0.390	0.074	−0.04	−1.00	0.19	−0.11
	(16.7)	(15.9)	(3.3)	(2.9)	(12.44)	(2.90)	(3.07)
Within-2SLS	0.60	−0.496	−0.106	0.19	−1.25	−0.04	0.47
	(17.0)	(13.0)	(0.5)	(6.4)	(17.96)	(0.51)	(7.14)
EC2SLS with Z_i and D_t	0.70	−0.406	0.067	0.14	−1.35	0.22	0.47
	(23.3)	(11.2)	(3.4)	(6.9)	(22.00)	(3.36)	(10.06)
EC2SLS-AR(1) with Z_i	0.67	−0.35	0.12	0.05	−1.07	0.37	0.14
	(16.6)	(11.9)	(3.9)	(1.8)	(6.7)	(3.5)	(1.75)
FD2SLS	0.51	−0.348	0.112	0.10	−0.71	0.23	0.21
	(9.5)	(12.3)	(3.5)	(2.9)	(7.49)	(3.05)	(2.68)
FD2SLS-KR	0.49	−0.348	0.095	0.13	−0.68	0.19	0.26
	(18.7)	(18.0)	(4.7)	(9.0)	(15.64)	(4.38)	(8.70)

Numbers in parentheses denote t-statistics.

III. Pooled Results

A. *Results Using Traditional Homogeneous Panel Estimators*

We begin by comparing the results of six traditional homogeneous estimators, all of which make slightly different assumptions about the error term in equation (4). These six traditional estimators are

1. OLS (without D_t and D_i), which ignores state-specific and time-specific effects;
2. OLS with D_t, which assumes time-period dummies reflecting structural shifts over time but ignores state-specific effects;
3. OLS with Z_i and D_t, which assumes that the state effects can be explicitly represented by the Z_i variables (such as race, religion, education, and tourism);
4. the Within estimator, which assumes the μ_i's and λ_t's are fixed effects that are modeled by time-period and state dummies (D_i and D_t);
5. the GLS estimator, which treats the μ_i's as random and the λ_t as fixed-effects, time-period dummies. (We also include the Z_i's and estimate the model using the instrumental variable method proposed by Hausman and Taylor (1981);
6. Finally, we assume that the μ_i's are random and the ν_{it}'s follow an AR(1) process, and we estimate the model by GLS as described in Baltagi and Li (1991).

As shown in section A of table 1, in the first regression, OLS—which ignores intertemporal and interstate taste differences—finds a very low short-run own price elasticity of −0.090 but a very large long-run price elasticity of −2.90. Inclusion of the time-period dummies in OLS (OLS with D_t) in table 1 does not materially affect the short-run and long-run price elasticities. The 0.95 coefficient on lagged consumption is no doubt biased because it is correlated with the omitted μ_i effects.[6] To illustrate the importance of explicitly modeling interregional taste variables, the third regression in table 1A—OLS with Z_i and D_t—introduces Z_i's for race, religion, education, and tourism to explain interstate taste differences. As expected, controlling for interregional effects with the Z_i's causes the coefficient on lagged consumption to decline from 0.95 to 0.90 and markedly reduces the long-run price elasticity to −1.95. Both the long-run neighboring price elasticity (0.55) and the income

[6] In addition, OLS has biased standard errors because it does not account for state-specific effects. See Moulton (1986).

elasticity (0.44) are statistically significant, and the estimates of the Z_i coefficients are generally plausible.[7]

But the list of Z_i's is most likely incomplete. The Within estimator in table 1 may be preferred in principle because it completely controls for time- and state-specific effects.[8] However, the cost of this is to lose all between-state variation and thus information on the source of interstate taste differences, which serve to identify the Z_i coefficients. Most significantly, the coefficient on lagged consumption drops even further to 0.83, dropping the long-run own price elasticity to -1.79. Note that another casualty of eliminating between-state variation was the statistical insignificance of the neighboring price effect (Pn), which depended on long-standing interstate tax differentials to identify its effects. Finally, the GLS estimates in table 1A treat the μ_i's as random effects and thereby incorporate between-state variation. For the Hausman and Taylor instrumental variable estimation (GLS with Z_i and D_t), the lagged consumption-coefficient estimate is 0.91, and the own long-run price elasticity is -2.00. Adjusting for first-order serial correlation on the remainder disturbances (GLS-AR(1)), the lagged consumption-coefficient estimate is 0.96, and the long-run own price elasticity is -2.09.

Interestingly, the traditional estimators as a group enjoy certain areas of conformity, but also raise troubling differences. For examples of conformity, the range of estimates on lagged consumption from 0.83 to 0.97 imply strong habit persistence. Furthermore, the long-run price elasticity is large, ranging from -1.79 to -2.98. On the other hand, estimates of long-run income elasticity range from statistically significant values of -1.00 to $+0.60$. An explanation for the anomalous results for income is that the between variation implies that low-income states, particularly in the South, are associated with high cigarette consumption. Estimators that emphasize between variation are more likely to produce negative income elasticities.

Traditional panel data estimators are subject to simultaneous equation bias due to the presence of lagged cigarette consumption. Interestingly, depending on the traditional estimator chosen, there are alternative ways by which simultaneous equation bias can arise. The OLS results are biased and inconsistent for either of two reasons:

(a) there exist interstate random effects (μ_i) that will surely be correlated with lagged consumption and possibly correlated with the other explanatory variables, and
(b) autocorrelation in the disturbance term ν_{it} in equation (4) introduces endogeneity between the ν_{it} and the lagged dependent variable.

In contrast, the Within estimator avoids the inconsistency arising in (a) from the μ_i's being correlated with the explanatory variables, because it sweeps away the μ_i's. However, the Within estimator is still subject to the inconsistency in (b) arising from serial correlation of the ν_{it}'s (see Nickell (1981) and, more recently, Kiviet (1995)). Whereas, the Hausman and Taylor GLS estimator recaptures estimates of the Z_i's lost by the Within estimator, it will be inconsistent due to either (a) or (b).[9] In fact, Hausman's (1978) test for specification error based on the difference between GLS and the Within estimator yields a $\chi^2_4 = 58.29$. This has a p-value of 0.0001 and decisively rejects the independence of the μ_i's and the explanatory variables. Consequently, we turn to instrumental variable methods that will correct for the inconsistency caused by reasons (a) or (b).

B. *Results Using 2SLS Type Panel Estimators*

A number of alternative instrumental variable estimators are designed to deal with the lagged consumption variable. The simplest is 2SLS, shown in table 1B, which differs from OLS only in that it assumes lagged consumption endogenous. Comparison of the OLS results in table 1A with the 2SLS results in table 1B show a substantial drop in the lagged-consumption coefficient from 0.97 to 0.85 and a drop in the long-run price elasticity from -2.90 to -1.37. The problem with simple 2SLS is that it does not account for the Z_i variables or individual state effects, any of which could result in omission bias. As illustrated by the 2SLS with Z_i and D_t results, these variables matter. With their inclusion, the lagged coefficient on consumption drops even further to 0.63 and the long-run own price elasticity is -1.31.

But even 2SLS with Z_i and D_t can yield potentially inconsistent estimates of our model if the Z_i's are an incomplete representation of the μ_i state effects. In addition, serial correlation of the ν_{it}'s will render our estimators asymptotically inefficient. Keane and Runkle (1992) (hereafter denoted by KR) suggest a modification of this 2SLS estimator that allows for any arbitrary type of serial correlation in the ν_{it}'s. Applying 2SLS-KR, the lagged coefficient on consumption decreases from 0.85 (for 2SLS) to 0.71, and the long-run own price effect decreases in absolute value from -1.31 (for 2SLS) to -1.07. The Within-2SLS finds an even smaller lagged consumption-coefficient estimate, a higher short-run own price elasticity in absolute value, and

[7] Appendix A reports the estimated coefficients of the Z_i variables in these and subsequent regressions. Among the various racial variables, blacks appear to have lower cigarette consumption than do whites. Among the religious variables, the Mormon ban on smoking seems supported by the data. Tourism is positively related to cigarette consumption, while education is statistically insignificant.

[8] The specific state and time dummies were tested for their significance jointly as well as separately. Both state and time dummies were significant with an observed F-statistic of 7.39 and a p-value of 0.0001 under the null distribution of $F(73, 1256)$. The observed F-statistic for the significance of state dummies (given the existence of time dummies) is 4.16, which has a p-value of 0.0001 under the null distribution of $F(45, 1256)$. The observed F-statistic for the significance of the time dummies (given the existence of state dummies) is 16.05, which has a p-value of 0.0001 under the null distribution of $F(28, 1256)$. These F-tests perform well even when the state effects are random. See Moulton and Randolph (1989). The results of these tests emphasize the importance of individual-state and time-period effects in the cigarette-demand equation.

[9] The Hausman/Taylor (1981) GLS estimator is an instrumental variable estimator with the following set of instruments: $[P_{it}, Y_{it}, Pn_{it}, P_{i,t-1}, Y_{i,t-1}, Pn_{i,t-1}, Z_i]$.

even lower long-run price elasticity. Clearly, completely controlling for state effects results in less-elastic price responses. Comparing the Within-2SLS estimates in table 1B with the Within estimates in table 1A, we note that the Within-2SLS estimator finds an even lower lagged-consumption estimate of 0.60 compared to 0.83, a corresponding lower long-run own price elasticity (−1.25 versus −1.79), and the absence of neighboring state's price effects. The Within estimator potentially suffers from bias in a dynamic model due to the correlation between lagged consumption and $\bar{\nu}_i$, where $\bar{\nu}_i$ is the average of the remainder disturbances across time. This bias disappears as T gets large. However, wiping out the μ_i's does not necessarily get rid of all endogeneity between the predetermined variables and the disturbances. Within-2SLS corrects for this by using instrumental variables.

Next, we apply a two-stage least squares procedure that assumes a one-way error-component model, that is, EC2SLS (see Hsiao (1986)). This method transforms the error by $\hat{\Omega}^{-1/2}$, where $\hat{\Omega}$ is a consistent estimator of the variance-covariance matrix of the disturbances, and then applies 2SLS using between and within variations in the exogenous variables and their lagged values as instruments. This method yields a lagged coefficient of consumption estimate of 0.70 and a long-run own price elasticity of −1.35. Allowing for the possibility of an AR(1) process on the remainder disturbances (ν_{it} in equation (4)) and still preserving the error-component structure on the disturbances, the EC2SLS-AR(1) procedure yields a lagged coefficient of consumption estimate of 0.67 and a long-run own price elasticity estimate of −1.07. Yet another method of controlling for state effects proposed by Anderson and Hsiao (1982) amounts to first differencing the data and then applying 2SLS using lagged values of the exogenous variables as instruments, which is denoted by FD2SLS.[10] Still another variant would be to allow for any arbitrary form of serial correlation in the first differenced disturbances in the manner of Keane/Runkle. This is denoted as the FD2SLS-KR estimator. Although the FD2SLS and the FD2SLS-KR estimates are quite similar, they differ appreciably from other 2SLS type estimators. For example, with FD2SLS-KR, the lagged coefficient of consumption is lower than that of Within-2SLS (0.49 compared to 0.60), and the long-run own price elasticity estimate declines to −0.68 versus −1.25 for Within-2SLS.[11]

Even though the first-difference type estimators may eliminate bias arising from state effects, it is important to recognize that it does so at a large information cost. First differencing the data eliminates the economic structure implied by the levels of the variables within any given time series. Thus, one worries whether these results implying implausibly weak habits persistence and dramatically lower long-run price elasticities are merely the result of a sanitized data set. For this reason, the forecast performance simulation in section V is instructive.

To summarize, comparing the 2SLS type estimators to their traditional counterparts, the lagged coefficient on consumption ranges between 0.49 to 0.85—much lower than the traditional pooled estimators which were in the range of 0.83 to 0.97. The long-run own price elasticity estimates are much less elastic, ranging between −0.68 and −1.37—much lower in absolute value than the traditional pooled estimates, which were in the range of −1.79 to −2.98. The long-run neighboring price effect ranges from an insignificant −0.04 to a significant 0.37 and appears generally lower than their traditional counterparts. For the long-run income elasticity, there is less variation in estimates among 2SLS type estimators than their traditional counterparts, giving a clear implication that cigarettes are a weakly normal good.

IV. Results Using Heterogeneous Estimators

Implicitly, all the pooled estimators in section III assume homogeneity of the parameters across states.[12] More recently, the fundamental assumption underlying pooled homogeneous parameters models has been called into question and alternative heterogeneous estimators has been proposed.[13] Pesaran and Smith (1995) argue that the dynamic pooled model can be biased because of heterogeneity in the parameters across each state. Furthermore, they propose that an average of the individual state regressions can lead to consistent estimates of the parameters as long as N and T tend to infinity. Table 2 summarizes the results of the individual states regressions and the Pesaran/Smith average estimates. The individual state regressions yield quite a wide range of long-run price elasticities, ranging from 5.46 to

[10] More instrumental variables can be obtained if the ν_{it}'s are not serially correlated by using predetermined instruments that are not correlated with the error term. See Arellano and Bover (1995) or Ahn and Schmidt (1995).

[11] Underlying the instrumental-variable estimation is always the question of whether the instruments are strictly exogenous with respect to the error term. In this case, this could be due to correlation with the μ_i's or the ν_{it}'s. Keane and Runkle (1992) suggest a Hausman (1978) type test for the strict exogeneity of the instruments based on the difference between Within-2SLS and first-differenced 2SLS. The latter estimator is consistent whether the instruments are predetermined or strictly exogenous with respect to the error term, whereas the former estimator is consistent only if the instruments are strictly exogenous. The χ^2_4 statistic obtained is 118.6, which is significant. Keane and Runkle also suggest testing for the null hypothesis H_0; $E(\mu_i/\text{set of instruments}) = 0$. This is based on the difference between 2SLS and first-differenced 2SLS. The former is consistent only if the μ_i's are not correlated with the set of instruments, whereas first-differenced 2SLS is consistent regardless. The χ^2_4 statistic is 96.6, which is also significant. This confirms the importance of controlling for these μ_i effects.

[12] A Chow-test for the equality of slope coefficients across countries yields an F-value of 2.32. The numerator of this F-statistic is based on the second-stage regression of 2SLS allowing for varying intercepts and common slopes under its restricted version, and varying intercepts and slopes under its unrestricted version. The denominator of this F-statistic is based on the unrestricted 2SLS residuals sums of squares. (See Wooldridge (1990).) Under the null hypothesis, this is distributed as $F(180, 1104)$. The observed F-statistic has a p-value of 0.0001, and the null is rejected.

[13] See, for example, Robertson and Symons (1992), who warned about the bias obtained from panel data methods when the estimated model is dynamic and homogeneous when in fact the true model is static and heterogeneous.

TABLE 2.—CIGARETTE DEMAND: HETEROGENEOUS PARAMETER ESTIMATES 1963–1992

	Short Run				Long Run		
	$\ln C_{it-1}$	$\ln P_{it}$	$\ln Pn_{it}$	$\ln Y_{it}$	$\ln P_{it}$	$\ln Pn_{it}$	$\ln Y_{it}$
Individual Countries OLS:							
Maximum	1.05	−0.85	0.71	0.15	−8.46	4.74	0.81
	(6.67)	(2.78)	(3.64)	(1.07)	(0.31)	(0.28)	(0.13)
Median	0.69	−0.24	0.06	−0.14	−0.57	0.10	−0.38
	(4.56)	(1.86)	(0.47)	(1.07)	(2.45)	(0.24)	(4.11)
Minimum	0.03	0.44	−0.61	−0.54	5.46	−7.38	−3.37
	(0.15)	(0.1)	(1.90)	(1.71)	(0.56)	(0.62)	(0.35)
Average	0.73	−0.28	0.09	−0.14	−0.79	0.25	−0.39
	(4.75)	(10.1)	(3.31)	(8.24)	(9.84)	(3.18)	(9.25)
Shrinkage OLS:							
Maximum	0.98	−0.16	0.09	−0.01	−4.84	2.62	−0.17
	(42.2)	(5.70)	(3.23)	(0.88)	(1.44)	(1.16)	(1.34)
Median	0.94	−0.11	0.03	−0.04	−1.76	0.42	−0.68
	(46.0)	(3.60)	(1.00)	(2.41)	(2.54)	(1.17)	(1.74)
Minimum	0.88	−0.04	−0.04	−0.08	−0.74	−0.71	−1.61
	(37.1)	(1.32)	(1.32)	(5.13)	(1.45)	(1.13)	(2.62)
Individual Countries 2SLS:							
Maximum	3.35	−1.07	0.70	1.22	−7.46	6.53	0.38
	(0.80)	(2.02)	(3.51)	(0.54)	(0.58)	(0.54)	(3.75)
Median	0.60	−0.34	0.11	−0.11	−0.55	0.08	−0.39
	(1.35)	(2.72)	(0.84)	(0.75)	(0.97)	(0.43)	(5.70)
Minimum	−0.31	0.52	−0.55	−0.66	5.23	−5.54	−1.88
	(1.06)	(1.24)	(1.51)	(3.25)	(0.20)	(0.24)	(0.73)
Average	0.65	−0.32	0.15	−0.05	−1.17	0.54	−0.16
	(0.83)	(7.42)	(3.36)	(0.68)	(2.28)	(2.02)	(0.68)
Shrinkage 2SLS:							
Maximum	1.61	−0.34	0.20	0.30	−6.69	4.97	4.94
	(10.5)	(3.83)	(2.86)	(3.55)	(0.94)	(0.77)	(0.04)
Median	0.88	−0.14	0.04	−0.05	−0.85	0.18	−0.47
	(9.34)	(1.71)	(0.70)	(0.76)	(2.20)	(0.13)	(2.80)
Minimum	0.64	0.08	−0.13	−0.20	13.78	−5.80	−1.95
	(4.34)	(1.00)	(1.78)	(2.77)	(0.04)	(0.49)	(1.06)

Numbers in parentheses denote t-statistics.

−8.46 for OLS and 5.23 to −7.46 for 2SLS. A wide range of long-run estimates is also apparent for the neighboring price and income elasticities. Pesaran and Smith's suggestion of using a simple average of the individual state estimates to obtain long-run elasticity estimates implies that the long-run 2SLS elasticities are −1.17 for own price, 0.54 for neighboring price, and −0.16 for income—while the corresponding average OLS elasticities are, respectively, −0.79 for own price, 0.25 for neighboring price, and −0.39 for income.

Using a quite different approach, Maddala et al. (1994) argue that Shrinkage estimators are superior to either the individual state (heterogeneous) estimates or the pooled (homogeneous) estimates especially for prediction purposes. In this case, one shrinks the individual estimates towards the pooled estimate using weights depending on their corresponding variance-covariance matrices. The shrinkage estimator suggested by Maddala et al. substantially reduces the wide dispersion of estimates found in the individual countries, which demonstrates that the effect of pulling individual estimates towards a common mean profoundly affects the estimates. The OLS Shrinkage estimates of the long-run price elasticity range from −0.75 to −4.84, while those of 2SLS range from 13.78 to −6.69. Considerable variation in the long-run estimates of neighboring price and income elasticities are also apparent.

In summary, the heterogeneous estimators (the individual 2SLS, the Pesaran/Smith average, and the Maddala et al. Shrinkage estimator) have the desirable property of allowing for differences among states, but the range of individual 2SLS estimates suggests that the individual state estimates are highly unstable and unreliable. Indeed, the instability of parameter estimates from individual time series has been observed quite commonly in a variety of demand studies,[14] providing a major argument for pooling. The Pesaran/Smith suggestion of using a simple average offers an alternative to the homogeneous estimators. Likewise, the Shrinkage estimator seems to provide a smaller and more plausible range of estimates than do individual time-series estimates. Nevertheless, ranges of Shrinkage 2SLS estimates for the long-run price elasticity of −6.69 to 13.78 are implausible. In contrast, the pooled estimators, which implicitly posit homogeneous coefficients, appear to provide, on balance, much more plausible estimates than their heterogeneous counterparts.

[14] For examples, see studies of gasoline demand (Baltagi and Griffin (1983)), natural gas (Balestra and Nerlove (1966)), and electricity (Taylor (1975)).

TABLE 3.—COMPARISON OF FORECAST PERFORMANCE

	1st Year		5th Year		10th Year		10-Year Average	
Ranking	Estimator	RMSE	Estimator	RMSE	Estimator	RMSE	Estimator	RMSE
1.	FD2SLS-KR	2.80	Within-2SLS	9.29	Within-2SLS	14.08	Within-2SLS	9.93
2.	FD2SLS	2.80	Within	11.57	OLS	16.11	OLS	11.80
3.	Within	3.20	OLS	11.75	Within	17.21	Within	12.11
4.	2SLS	3.32	GLS	12.73	GLS	19.14	GLS	13.20
5.	EC2SLS-AR(1)	3.54	FD2SLS-KR	12.81	GLS-AR(1)	23.65	FD2SLS-KR	14.44
6.	Within-2SLS	3.60	FD2SLS	12.92	FD2SLS-KR	24.03	FD2SLS	14.70
7.	Average OLS	3.68	Shrinkage 2SLS	13.67	Shrinkage 2SLS	24.15	GLS-AR(1)	15.04
8.	OLS	3.68	GLS-AR(1)	13.89	FDSLS	24.84	Shrinkage 2SLS	15.09
9.	Shrinkage OLS	3.71	Shrinkage OLS	15.02	2SLS	26.66	2SLS	16.92
10.	GLS	3.73	2SLS	15.40	Shrinkage OLS	28.82	Shrinkage OLS	16.93
11.	Average 2SLS	3.79	Average OLS	15.47	Average OLS	29.46	Individual OLS	16.93
12.	Shrinkage 2SLS	3.88	Average 2SLS	15.49	Average 2SLS	29.66	Average OLS	17.39
13.	GLS-AR(1)	3.95	EC2SLS-AR(1)	16.47	EC2SLS-AR(1)	30.10	Average 2SLS	17.45
14.	Individual OLS	4.04	No Change	16.59	No Change	32.54	EC2SLS-AR(1)	18.13
15.	No Change	4.50	Individual OLS	18.08	Individual OLS	34.75	No Change	19.05
16.	Individual 2SLS	4.89	Individual 2SLS	27.17	Individual 2SLS	130.8	Individual 2SLS	43.84

RMSE $\times 10^2$.

V. Comparison of Forecasts

An important and frequently underutilized criteria is the forecast properties of alternative estimators. In this section, we use the prediction-performance criteria to help us choose among alternative estimators with quite disparate price elasticity implications. Given the large data set of 46 states for over thirty years, we estimate the above models for truncated data sets and then apply each model to an out-of-sample forecast period. Because the estimators imply very different long-run elasticities, it seems particularly useful to contrast their forecast performance over time periods as far out as ten years.

Table 3 gives a comparison of various predictors obtained by estimating the model without the last ten years of data and then applying these models to out-of-sample forecasts of cigarette consumption over these ten years. The root mean square errors (RMSEs) are calculated for the resulting predictions. Because the ability of an estimator to characterize long-run as well as short-run responses is at issue, the average RMSE is calculated across the 46 states at different forecast horizons. Specifically, each model was applied to each state, and out-of-sample forecasts for ten years were calculated. The relative forecast rankings are reported in table 3 after one year, five years, and ten years.[15] The overall average ranking for the full ten-year period is also reported. To provide some relative comparison basis, we also include a naive model that sequentially forecasted ''no change'' in a state's cigarette consumption per capita. In comparing the relative performance of the various estimators, one can analyze these results from the following perspectives: heterogeneous versus homogeneous, and one-year-ahead forecasts versus long-run forecasts.

A comparison of the heterogeneous versus homogeneous estimators reveals some very interesting patterns. Of the heterogeneous estimators, individual OLS and individual 2SLS perform uniformly poorly vis-a-vis both the homogeneous and other heterogeneous estimators. Indeed, for the fifth- and tenth-year forecasts, individual OLS and individual 2SLS have the distinction of being the only estimators to perform worse than the naive ''no change'' model. Such a finding may seem counterintuitive because, by definition, individual state regressions give the best fit over the sample period. Even in out-of-sample forecasts, it would seem that individual state regressions would out-perform homogeneous panel estimators because the latter place relatively little weight on the data for any one state. Why then, particularly in five- and ten-year forecasts, do individual state regressions perform so poorly?

The explanation for this seeming paradox is that individual state regressions are highly unstable between the twenty- and thirty-year samples, especially as they relate to long-run elasticities. Table 4 reports the absolute difference in the implied short- and long-run elasticities for the various estimators. We use absolute instead of actual differences because, for individual state regressions, we compute the absolute difference in the parameter estimates and then average it across states to provide a meaningful basis for comparison. Table 4 reports the various estimators ranked by the absolute change in the long-run price elasticity. Clearly, individual OLS and 2SLS yield highly unstable long-run estimates, explaining why they do so poorly in ten-year forecasts. In contrast, the strength of the homogeneous panel estimators as a group is their relative stability. Thus, as has been widely confirmed in other contexts,[16] there are real gains from pooling particularly when the time series is relatively short.

The performance by the other heterogeneous estimators is mixed. The Pesaran/Smith ''Average OLS'' and ''Average

[15] These predictions were intercept-adjusted for each state. Additionally, all estimators have zero forecast errors for 1982.

[16] See Balestra and Nerlove (1966), Taylor (1975), and Baltagi and Griffin (1997).

TABLE 4.—COMPARISON OF ABSOLUTE DIFFERENCES IN PARAMETER ESTIMATES: 20- VS. 30-YEAR SAMPLE

		Short-Run Difference			Long-Run Difference		
Ranking*	Estimator	ln P_{it}	ln Pn_{it}	ln Y_{it}	ln P_{it}	ln Pn_{it}	ln Y_{it}
1.	FD2SLS-KR	0.04	0.11	0.05	0.06	0.14	0.12
2.	Within-2SLS	0.06	0.19	0.10	0.07	0.23	0.21
3.	GLS	0.03	0.03	0.00	0.16	0.54	0.12
4.	Within	0.11	0.06	0.09	0.17	0.15	0.13
5.	FD2SLS	0.04	0.10	0.01	0.18	0.06	0.09
6.	Average OLS	0.03	0.18	0.11	0.28	0.20	0.35
7.	2SLS	0.14	0.17	0.11	0.34	0.31	0.38
8.	OLS	0.03	0.05	0.03	0.38	0.83	1.00
9.	EC2SLS-AR(1)	0.09	0.17	0.08	0.59	0.14	0.25
10.	GLS-AR(1)	0.04	0.06	0.03	0.59	0.85	1.11
11.	Average 2SLS	0.03	0.13	0.01	0.70	0.10	0.07
12.	Individual OLS	0.20	0.24	0.21	1.12	1.15	0.59
13.	Individual 2SLS	0.24	0.25	0.33	1.13	1.29	0.73
14.	Shrinkage OLS	0.12	0.15	0.10	1.24	0.41	0.74
15.	Shrinkage 2SLS	0.06	0.06	0.07	4.50	3.30	0.71

*This ranks the estimators by the absolute difference in the long-run price elasticity.

2SLS'' estimators rank seventh and eleventh, respectively in one-year-ahead forecasts. Yet, for the five- and ten-year forecasts, they have dropped to eleventh and twelfth and overall rank twelfth and thirteenth. The deteriorating performance of the Pesaran/Smith average estimator arises because of the parameter-instability problem of the individual state regressions shown in table 4. The shrinkage 2SLS estimator appears to have the reverse problem of the ''Average'' estimator. For one-year forecasts, shrinkage 2SLS ranks twelfth, yet, for the five- and ten-year forecasts, it ranks seventh. (Overall, it ranks eighth.) Shrinkage OLS ranks ninth for one-year and five-year forecasts, tenth for the ten-year forecast, and tenth overall. The relatively poor performance of the shrinkage estimators can be attributed to its reliance upon the individual state parameter estimates. Thus, what seemed an advantage to the shrinkage estimator—that is, placing some weight on the individual state regressions—becomes a liability when parameter instability is severe. While the coefficients of the short-run estimates were relatively stable, the extreme long-run parameter instability shown in table 4 could be attributed to three states for which the lagged dependent-variable coefficient was close to 1.

The overall RMSE forecast rankings offer a strong endorsement for the homogeneous estimators due in large part to their parameter stability. Within-2SLS ranks first, followed by OLS, Within, GLS, and FD2SLS estimators. In fact, the top six estimators for one-, five-, ten- and average ten-years forecasts are homogeneous parameter estimators. The finding that Within-2SLS gives the lowest RMSE for five-, ten-, and overall ten-year average suggests that controlling for state effects and endogeneity are important. It also provides some support for a less elastic long-run price elasticity in the range of -1.25.

The forecast results provide comfort to researchers applying homogeneous panel estimators, both as indicated by the sizeable range of parameter estimates in table 1 and forecast performance in table 3. But the choice of which estimator becomes paramount. Simply because a particular estimator is theoretically capable of dealing with a wider variety of potential biases (such as the first-difference 2SLS model with Keane/Runkle adjustment (FD2SLS-KR)), it does not necessarily provide the best forecasts. For example, FD2SLS and FD2SLS-KR, which control for state effects and endogeneity, deteriorate sharply as the forecast horizon is extended beyond one year.[17] The 2SLS type estimators depend critically on the quality of the instruments. One measure of the quality of these instruments is the R^2 from the first stage of 2SLS. For 2SLS, the set of instruments is P_{it}, Pn_{it}, Y_{it}, and their lagged values. The R^2 for the first stage of 2SLS is 0.31. For Within-2SLS written as 2SLS with time and state dummy variables, this R^2 rises to 0.89. Note that FD2SLS has a different dependent variable, but the R^2 for the first stage of FD2SLS is 0.26. Not surprisingly, Within-2SLS performs much better in forecast applications than do the other 2SLS type estimators. Interestingly, the more traditional Within, OLS, and GLS estimators also perform quite well, ranking second, third, and fourth, respectively, overall in forecasting performance and yet offer no correction for endogeneity.

The traditional pooled estimators (OLS, Within, and GLS) results of table 3 are comforting as they systematically perform well in forecasting for five years or longer. Furthermore, it is noteworthy that OLS (which is potentially most impacted by bias) is second only to the Within-2SLS for the ten-year average forecast performance. Our explanation for this seeming paradox is that, while OLS may be more susceptible to bias, it relies heavily upon between state variation. If one accepts the notion that the between variation tends to capture long-run responses, it should not be surprising that it would perform well in long-term

[17] FD2SLS-KR requires estimation of the covariance matrix of error terms, which is 20 × 20 for the data used for forecasting and 30 × 30 for the entire sample. It is unlikely that 46 cross-section observations will generate a reliable estimate for a matrix of this size. As one of the referees suggest, this might explain why FD2SLS-KR often performs worse than Within-2SLS does.

forecasts. Thus, the researcher must keep in mind the potential trade-off between bias and the source of variation affecting a given estimator. By the same argument, it should not be surprising that FD2SLS type estimators perform well in one-year forecasts, yet fail to capture long-term responses.

The finding that the traditional pooled estimators (OLS, Within, and GLS) performed relatively well in this application echoes a similar finding in Baltagi and Griffin (1997) for an international panel of gasoline consumption. In that study, these three estimators were in the top four when ranked by ten-year average forecast performance. On the other hand, they found that heterogeneous estimators did not fare particularly well in long-run forecast applications.

Turning to the important question of the long-run price elasticity, we note that for both the five- and ten-year forecasts, Within-2SLS (which implies a long-run price elasticity of -1.25) significantly outperforms the next-best estimators.[18] This result is comforting both intuitively and econometrically. The Within-2SLS estimator avoids the problem of endogeneity of the lagged-consumption term and the heterogeneity arising from intertemporal and interstate effects.

VI. Summary and Conclusions

Like the Baltagi and Griffin (1997) international gasoline-consumption panel, the results of this paper confirm the value of panel data sets and justify the emphasis given to pooled estimators. Even with a relatively long time series, heterogeneous models for individual states tend to produce implausible estimates with inferior forecasting properties. Our explanation for why pooled models—which posit homogeneous parameters—outperform their heterogeneous counterparts centers on the relative variability of the data between individual time series and panels. Using an RMSE criterion, the efficiency gains from pooling appear to more than offset the biases due to interstate heterogeneities. Interestingly, even with thirty years of data and dynamic demand goods with substantial lags, individual state time series perform poorly. Even panel estimators that posit heterogeneous coefficients such as the Pesaran/Smith average estimator and Maddala's shrinkage estimator seem to be inferior in forecasting performance when compared to the traditional pooled estimators.

While finding rather clear evidence on the question to pool or not, our answer as to which pooled estimator is more problematic. With long-run price elasticities ranging from -0.68 to -2.98, the choice among homogeneous estimators clearly matters. We offer the following tentative findings.

- The Within-2SLS estimator, which finds a long-run price elasticity of -1.25, performs best in forecast exercises by a significant margin and would seem to be the preferred homogeneous estimator. We are, however, skeptical about labelling Within-2SLS as the "preferred" panel estimator, given its relatively poor performance in our gasoline-demand study.
- The gain from 2SLS depends critically on the quality of the 2SLS instruments. For cigarettes, while Within-2SLS was the top forecast performer, other 2SLS estimators performed poorly. For gasoline, all of the 2SLS estimators performed poorly.
- In both studies, three of the top four forecast performers were OLS, GLS, and Within. This finding should give comfort to applied researchers who routinely employ the traditional pooled estimators.

[18] Interestingly, the next-closest rivals, OLS and Within, give relatively similar forecast performance over the ten-year period. Yet, they imply very different long-run price elasticities (2.90 versus -1.79) and income elasticities (-1.0 and 0.60). Christ (1966) pointed out that, in the context of macroeconometric models, models with very different implied short- and long-run dynamics can yield similar RMSEs in forecast applications.

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APPENDIX A—ESTIMATED COEFFICIENTS OF Z_i IN VARIOUS MODELS

Model	OLS	GLS	GLS-AR(1)	2SLS	2SLS-KR	EC2SLS	EC2SLS-AR(1)
% Asian	−0.0057	−0.0049	−0.0013	−0.0054	−0.0029	−0.0133	−0.0103
	(2.8)	(2.5)	(0.9)	(2.0)	(0.4)	(5.1)	(1.2)
%Indian + Eskimo	0.0030	−0.0030	−0.0022	−0.0081	−0.0085	−0.0074	−0.0083
	(3.7)	(3.7)	(3.7)	(5.3)	(2.5)	(6.5)	(2.3)
% Black	−0.0031	−0.0003	−0.0002	0.0001	0.0005	−0.0003	0.0002
	(2.6)	(2.4)	(2.5)	(0.8)	(0.9)	(2.3)	(0.4)
% Hispanic	−0.0006	−0.0005	−0.0003	−0.0010	−0.0025	−0.0014	−0.0016
	(1.9)	(1.7)	(1.2)	(2.2)	(2.0)	(3.7)	(1.1)
% Mormon	−0.0006	−0.0006	−0.0004	−0.0020	−0.0032	−0.0018	−0.0023
	(4.1)	(4.0)	(3.3)	(5.6)	(5.0)	(7.5)	(3.4)
% Catholic	−0.0002	0.0002	0.0001	0.0004	0.0008	0.0007	0.0005
	(1.1)	(1.0)	(0.5)	(1.6)	(1.2)	(3.3)	(0.6)
% South Baptist	0.0003	0.0002	0.0002	−0.0008	−0.0019	0.0003	−0.0007
	(1.5)	(1.2)	(1.1)	(2.7)	(2.5)	(1.4)	(0.8)
% Methodist	0.0013	0.0004	−0.0002	−0.0014	−0.0022	−0.0002	−0.0004
	(0.2)	(0.1)	(0.5)	(1.7)	(0.9)	(0.2)	(0.1)
% Church of Christ	−0.014	−0.0012	−0.0003	−0.0013	−0.0039	−0.0040	−0.0034
	(1.2)	(1.0)	(0.3)	(0.9)	(0.8)	(2.9)	(0.7)
% Episcopalian	−0.0044	−0.0037	−0.0006	−0.0019	−0.0057	−0.0094	−0.0064
	(2.7)	(2.3)	(0.5)	(0.9)	(0.9)	(4.6)	(1.0)
% Lutheran	0.0019	−0.0018	−0.0006	−0.0045	−0.0063	−0.0055	−0.0063
	(3.9)	(3.6)	(1.8)	(4.7)	(3.3)	(7.1)	(3.0)
% Jewish	0.0009	0.0008	0.0002	0.0023	0.0055	0.0033	0.0032
	(1.4)	(1.9)	(0.3)	(2.3)	(1.9)	(3.8)	(1.1)
% Education	0.0003	0.0005	0.0006	0.0049	0.0005	−0.0001	0.0047
	(0.1)	(0.1)	(0.2)	(1.0)	(0.03)	(0.03)	(0.3)
Tourism	0.0007	0.0006	0.0002	0.0020	0.0030	0.0024	0.0027
	(3.5)	(3.2)	(1.7)	(4.9)	(3.8)	(7.3)	(3.3)

All models in this table have time dummies.