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Abstract

This paper examines price adjustment behavior in the magazine industry. In a frequently cited study, Cecchetti (1986) constructs a reduced-form (*S,s*) model for firms. Cecchetti assumes that a firm's pricing rules are fixed for non-overlapping three-year intervals and estimates the model using a conditional logit specification from Chamberlain (1980). The estimates are inconsistent, however, due to the state-dependent specification of the model. I illustrate the econometric problems in Cecchetti's results through a Monte Carlo exercise and then suggest a method for producing consistent estimates based upon Heckman and Singer (1984). The corrected results provide strong support for models of state-dependent pricing.

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1 Introduction

In a frequently cited study of price adjustment, Cecchetti (1986) uses data on magazine cover prices to examine determinants of the frequency of price adjustment. Based upon his empirical results, Cecchetti makes two conclusions: 1) higher inflation leads to more frequent price adjustment and 2) the real cost of a nominal price change varies with either the frequency of adjustment or the size of a real price change. The empirical techniques used by Cecchetti, however, are inconsistent due to the presence of state-dependent covariates in the estimation. This paper will outline the econometric problems inherent in Cecchetti's results, test for various forms of heterogeneity in the magazine data, and offer a procedure to obtain consistent estimates. The corrected results confirm Cecchetti's first conclusion – providing strong evidence for models of state-dependent pricing – but do not yield evidence on the structure of price adjustment costs.

Cecchetti's paper is one of the few empirical studies of price determination that attempts to estimate a model using microeconomic data.[1] A primary reason for the lack of empirical work is the difficulty in obtaining transaction price data. The data on magazine cover prices, in addition to being easily collectable, possess the desired characteristics for the study of price changes. Magazine cover prices change at discrete intervals, remain fixed for long periods of time, and are not the result of an auction process. However, one potential drawback is that the magazine industry does not rely solely on revenue generated through transactions occurring at the cover price. Subscription sales and advertising fees provide a large portion of the revenues for the industry.[2]

Cecchetti addresses two questions stemming from the theoretical literature of price de-

[1] Recent papers focusing on the estimation of price adjustment costs include Aguirregabiria (1999), Slade (1998), and Willis (2000).

[2] Subscription sales account for about 70 percent of circulation on average over the sample period. In recent years advertising revenue has accounted for over 70 percent of total revenue for magazines in Cecchetti's sample.

termination for monopolistically competitive firms. The first concerns the response of the frequency of adjustment to increases in general price inflation. Theory demonstrates that firms will adjust by larger amounts when faced with higher inflation, holding fixed the size of the adjustment costs, but theoretical models do not point to a clear relationship between inflation and the frequency of adjustment.[3] The second question pertains to the appropriate structure of the cost of price adjustment. Several theoretical studies have examined the size of a price adjustment cost necessary for a nominal demand shock to produce a certain response for real variables.[4] Providing empirical evidence on price adjustment costs, however, is much more challenging due to the lack of industry data and precise cost models. Obtaining estimates of these adjustment costs would provide useful evidence on the degree of price rigidity for firms. In addition, these estimates of adjustment costs could be used to study the aggregate implications of monetary shocks for real output.

The foundation of Cecchetti's empirical analysis is based on a target-threshold model from Iwai (1981). This model employs threshold barriers to signal when the price should be changed. If the optimal price surpasses a fixed distance from the current setting, then the price is adjusted. Prices are not constantly updated because of the presence of "menu costs," which could relate specifically to the physical costs of implementing price changes or to a broader variety of costs associated with information gathering costs and managerial costs necessary for the firm to make an fully informed optimization decision.

The firm's probability of a price change is derived from the optimal pricing decision. The probability can be expressed as a function of the change in the optimal price and the distance between the previous return point and the current threshold barrier of the (S, s) model. An analytic solution for the change in the optimal price, expressed in terms of observable variables, is obtained, but the distance between optimal (S, s) barriers is not observed. This unobserved "variable" represents the optimal pricing rules set by firms

[3]See Sheshinski and Weiss (1977,1983).

[4]See Blanchard and Kiyotaki (1987) and Ball and Romer (1990).

each period, which are inherently functions of the state variables of each firm's dynamic problem. Cecchetti identifies the model by assuming that the optimal pricing rules are constant over non-overlapping three-year increments. This assumption leads to a fixed-effects specification to control for the unobserved heterogeneity resulting from firm-specific optimal pricing rules. Due to the small number of observations per fixed-effect group (3 annual observations), Cecchetti uses a conditional logit estimation procedure described by Chamberlain (1980) to account for the presence of heterogeneity. However, in a subsequent paper, Card and Sullivan (1988) show that the presence of state-dependent covariates, which are included in Cecchetti's specification, leads to inconsistent estimates.[5] The loss of consistency nullifies the results of Hausman tests used to support Cecchetti's identification assumption.

I obtain consistent estimates using the approach of Heckman and Singer (1984). This procedure is based upon a random-effects specification, where the distribution of individual effects is assumed to be discrete. Within the estimation procedure, the discrete mass point distribution is estimated along with the other coefficients of interest. I perform two Monte Carlo exercises to illustrate the benefits of this approach. When applied to the magazine data, however, this procedure does not produce results significantly different from the unconditional logit model with no fixed effects

A final model is estimated based upon an alternative specification of heterogeneity. I specify a fixed-effects logit model with dummy variables to control for aggregate year effects and heterogeneity across magazines, rather than across magazine-specific 3-year intervals. These estimates provide strong support for models of state-dependent pricing, but they do not address the question concerning the structure of price adjustment costs.

[5] While a subset of econometricians are well-aware of this result, in general practice the problems introduced by state dependence are not often recognized. For example, Greene (1999) cites Cecchetti (1986) as a good empirical application of Chamberlain's conditional logit estimation procedure.

2 Model

In specifying a model for the pricing decision of a monopolistically competitive firm, the presence of price-adjustment costs and future uncertainty indicate the need for a dynamic-programming framework. In such a model, a firm chooses its price by maximizing the expected present discounted value of current and future profits, factoring in the price adjustment cost to be paid if adjustment occurs. Sheshinski and Weiss (1983) specify a general set of conditions where it is equivalently optimal for the firm to use a target-threshold (S, s) policy where adjustment occurs when the firm's price crosses an optimal barrier.

Cecchetti uses a target-threshold model described by Iwai (1981). In this model, firms develop a rule dictating that the price at time t, P_t, should be changed when it is a certain distance from the short-term optimal price, P_t^*. The short-term optimal price is defined as the price that would be set without adjustment costs. Define $z_t = log(P_t^*/P_t)$ as the measure of the distance between the actual price and optimal price. Let h_t^c be the maximum value z_t can reach before the price will be changed and h_t^0 be the prescribed value of z_t to be attained when the price change occurs. The optimal reset value, h_t^0, may be equal to zero, but if prices tend to drift upward, the firm will likely choose to raise the price above the optimal price in order to reduce the number of adjustments, thereby reducing the incidence of paying adjustment costs. In this situation, h_t^0 would be negative.

The probability of observing a price change can be written as the probability of z_t rising above h_t^c, indicating that the distance between the current price and the optimal price has surpassed the limit established by the (S, s) rule. This probability can also be rewritten in terms of comparing the distance P_t^* has moved since the last price change at time $\tilde{t}$ to the distances between the previous return point, $h_{\tilde{t}}^0$, and the current cutoff rule, h_t^c.[6]

[6] Recall that $z_t = \log P_t^* - \log P_t$. P_t was set in period $\tilde{t}$ according to the reset value $h_{\tilde{t}}^0 = \log P_{\tilde{t}}^* - \log P_t$. Therefore, we can substitute for z_t using $\log P_t^* - \log P_{\tilde{t}}^* + h_{\tilde{t}}^0$.

The problem with this setup, noted by Cecchetti, is that the rule should change over time as the firm reoptimizes. Assumptions about the timing of rule changes will lead to the specification of unobserved heterogeneity in the estimation.

For firm i, the probability of a price change at time t is as follows:

$$\begin{aligned} \Pr(y_{i,t} = 1) &= \Pr\left(z_{i,t} \geq h^c_{i,t}\right) \\ &= \Pr\left(\Delta \log P^*_{i,t,\tilde{t}} \geq h^c_{i,t} - h^0_{i,\tilde{t}}\right) \end{aligned} \tag{1}$$

where $y_{i,t}$ is a dummy variable equal to 1 if firm i changed its price at time t, $\Delta \log P^*_{i,t,\tilde{t}}$ is the cumulative change in the optimal price since the last price change at time $\tilde{t}$, and $h^0_{i,\tilde{t}}$ is the return point used at the time of the previous price change.

To solve for P^*, each firm is assumed to be a monopolistic competitor with the following demand $\left(Q^d_{i,t}\right)$ and cost functions $(C\left(Q_{i,t}\right))$:

$$Q^d_{i,t} = \left(\frac{P_{i,t}}{\bar{P}_t}\right)^b X^\gamma_t \tag{2}$$

$$C\left(Q_{i,t}\right) = Ae^{\delta t} Q^\alpha_{i,t} w_t \tag{3}$$

where $Q_{i,t}$ represents firm output, $P_{i,t}$ is the firm's price, $\bar{P}_t$ is the aggregate price level, X_t is total industry sales, δ is rate of technological progress, w_t is the input price, and b, γ, A, and α are constants. The demand and cost equations are substituted into the firm's profit function. Maximization of this function with respect to the price allows the calculation of $\log P^*_{i,t}$. Cecchetti assumes that P_t and w_t increase at the same constant rate and derives the change in optimal prices as

$$\Delta \log P^*_{i,t,\tilde{t}} = b_1 T_{i,t,\tilde{t}} + b_2 \pi_{i,t,\tilde{t}} + b_3 \dot{X}_{i,t,\tilde{t}} + u_{i,t} \tag{4}$$

where $T_{i,t,\tilde{t}}$ is the time since the previous price change for magazine i, $\pi_{i,t,\tilde{t}}$ is the cumulative inflation since the last price change, $\dot{X}_{i,t,\tilde{t}}$ is the cumulative percentage change in industry sales since the last price change, and $u_{i,t}$ is a stochastic error. Cecchetti states that the stochastic error term represents components of the optimal pricing decision that are not contained in the demand and cost functions.

Substitution into equation (1) yields

$$\begin{aligned} S_{i,t} &= \Delta \log P^{*}_{i,t,\tilde{t}} - \left(h^{c}_{i,t} - h^{0}_{i,\tilde{t}}\right) \\ &= b_1 T_{i,t,\tilde{t}} + b_2 \pi_{i,t,\tilde{t}} + b_3 \dot{X}_{i,t,\tilde{t}} + u_{i,t} - \left(h^{c}_{i,t} - h^{0}_{i,\tilde{t}}\right) \end{aligned} \tag{5}$$

By assuming that $u_{i,t}$ has a logistic distribution, the estimating equation is

$$\Pr\left(y_{i,t} = 1\right) = F\left(\bar{S}_{i,t}\right) \tag{6}$$

where F is the logistic function and $\bar{S}_{i,t} = S_{i,t} - u_{i,t}$.

3 Methods

In order to estimate equation (6), the unobserved optimal pricing rules $\left(h^{c}_{i,t} - h^{0}_{i,\tilde{t}}\right)$ must be identified. These rules represent the policy functions that solve the firm's dynamic optimization problem, and as such, they are implicit functions of the state variables in the firm's current information set. As the information set is updated over time, these rules will necessarily by modified as the firm reoptimizes. If these pricing rules are not accounted for in the estimation, the results will be subject to standard omitted variable bias.

Cecchetti argues that in the short run, a firm's optimal pricing rules are largely based on long-term expectations formed over several previous years. Based upon this interpretation, his identifying assumption is that pricing rules for a magazine are fixed in non-overlapping three-year increments. He can therefore treat the pricing rules as a fixed effect in his estimation procedure. In some cases, a fixed effect can be controlled for in estimation through differencing or dummy variables. Unfortunately, differencing does not lend itself to nonlinear models of the type here. Chamberlain (1980) illustrates a second problem, related to the size of the sample. In a panel data set where the number of individuals (N)

is large and number of observations per individual ($\bar{T}$) is small, nonlinear models do not possess the same consistency property (for fixed $\bar{T}$) as the linear fixed-effect model. For a dataset in which there are 2 observations per individual, Chamberlain shows that in a simple model with one covariate, the coefficient estimate using a logit distribution will be double the true value.

3.1 Cecchetti's estimation procedure

Cecchetti estimates his model using a method proposed by Chamberlain (1980). Chamberlain describes a fixed-effects specification for situations in which the number of observations per individual is small. Using the logistic function, the sum of the dependent variable over the sample for an individual serves as a sufficient statistic for the fixed-effects term. By conditioning on this sum, the fixed-effect term falls out of the conditional probability. The conditional likelihood function is then constructed as the product of the individual probabilities and maximized in nonlinear fashion. The estimates are consistent for data in which $\bar{T}$ is greater than or equal to two. The disadvantage of this estimation technique is that the fixed-effects coefficients are not estimated. Also, whenever the conditioning summation equals zero or $\bar{T}$, the probability for the individual is degenerate. Thus, the results of the conditional fixed-effects specification cannot be directly compared to results of unconditional logit estimates.

The inconsistency of Cecchetti's estimates arises due to the presence of state-dependent covariates. The cumulative variables measuring the number of years since the last price change $\left(T_{i,t,\tilde{t}}\right)$, more commonly referred to as *duration* in the literature; cumulative inflation since the last price change $\left(\pi_{i,t,\tilde{t}}\right)$; and cumulative percentage change in sales since the previous change $\left(\dot{X}_{i,t,\tilde{t}}\right)$, are all functions of lagged dependent variables as their values are based on the residing states in the past.[7] Card and Sullivan (1988) have shown that

[7]For example, the duration term can be expressed as $T_{i,t,\tilde{t}} = (1 - y_{i,t-1}) * T_{i,t-1,\tilde{t}} + 1$.

the conditional likelihood approach cannot be extended to the logistic model when one of the explanatory variables is state dependent. The minimal sufficient statistic for the fixed effect, in all but a few exceptional cases, is the entire set of data.[8] Thus, the Chamberlain specification, conditioning on the sum of the dependent variable for the individual, will not provide consistent estimates for the determinants of price adjustment.

The lack of consistency invalidates Hausman tests used by Cecchetti to support his model specification over several alternatives. The two alternative models tested contain simpler heterogeneity assumptions than described in the model above. One model contains a single constant term, assuming that there are no fixed effects across firms or over time. The second model includes a dummy variable for each magazine firm. Both of these alternative models are nested within Cecchetti's model. The difference is that the two alternative models can be estimated using the unconditional likelihood function, while Cecchetti estimated his model using Chamberlain's conditional likelihood method due to the small number of observations per "individual." The Hausman procedure tests whether the parameter vectors of two nested models are significantly different under the null that both models are consistent and the model with fewer parameters is efficient. Since the Chamberlain fixed-effect specification is not consistent, this test cannot be used to reject a simpler structure.

3.2 Heckman-Singer method

To obtain consistent estimates, I directly account for the individual-specific "variable" in the unconditional likelihood function using a random-effects specification to model Cecchetti's assumption that policy rules do not change over non-overlapping three year periods. Several methods exist where the distributional shape of an individual effect is assumed, and

[8]The exceptional cases consist of situations where the state-dependent covariates are not functions of the relevant state variables for the policy function, i.e. the coefficients for these variables in the logistic function are equal to zero.

then the effect is integrated out of the likelihood function. Heckman and Singer (1984) propose a procedure that abstracts from the assumption of a specific parametric representation of the distribution of the random effect by allowing for a partial parametric specification. This specification allows the unknown distribution to be represented non-parameterically by a step function. In this manner the probability density function is approximated by a discrete distribution with a certain number of mass points, and estimates are made for the location and density of each point. Lindsay (1983a, 1983b) shows that for this type of problem, the maximum of the likelihood function will contain a distribution with a finite number of mass points. The precise number of mass points can be determined by beginning with one support (i.e. no heterogeneity) and working upward. The location of an additional mass point is determined by finding the value that maximizes the Gauteaux derivative.[9] If the maximal value of the derivative is less than or equal to zero, then no more mass points are necessary. Although the distribution of the individual effects is not likely to be well characterized by the step function, Heckman and Singer have shown through Monte Carlo experiments that the coefficients of the other explanatory variables can be estimated with great precision.

3.3 Monte Carlo exercise

A Monte Carlo study illustrates the problems induced by state dependence in Cecchetti's estimates and the benefits of the Heckman-Singer estimation procedure. The "data" is constructed using Cecchetti's logit specification and data on inflation and magazine industry sales. From equations (5) and (6), the probability of a price change is expressed as

$$\Pr\left(y_{i,t}=1\right)=\frac{\exp\left(a_{i,t,\tilde{t}}+b_1 T_{i,t,\tilde{t}}+b_2\pi_{i,t,\tilde{t}}+b_3\dot{X}_{i,t,\tilde{t}}\right)}{1+\exp\left(a_{i,t,\tilde{t}}+b_1 T_{i,t,\tilde{t}}+b_2\pi_{i,t,\tilde{t}}+b_3\dot{X}_{i,t,\tilde{t}}\right)} \tag{7}$$

[9] See Heckman and Singer (1984) for details.

where $a_{i,t,\tilde{t}} \equiv -\left(h^c_{i,t} - h^0_{i,\tilde{t}}\right)$. The key assumption concerns the specification of the agent's optimal pricing rules, $a_{i,t,\tilde{t}}$. For this exercise, Cecchetti's assumption of three-year fixed pricing rules is used. The value of $a_{i,t,\tilde{t}}$ for every non-overlapping three-year period is randomly drawn from a uniform distribution in the range $[-8, -2]$, which roughly corresponds to average values backed-out from Cecchetti's estimation using magazine data.[10] Cecchetti's parameter estimates are taken as "truth."[11] For this experiment, 10,000 datasets are generated, each composed of 38 firms simulated over 27 years.[12] Firm-specific randomly generated individual effects are selected for each non-overlapping three-year period. The covariates are created sequentially as a function of the lagged dependent variable and actual data on aggregate inflation and industry sales. I estimate the coefficients using three different estimation methods: Chamberlain's fixed-effects conditional logit, unconditional logit, and the Heckman-Singer random-effects logit specification. The results are presented in Table 1.

Column 1 lists the values used in constructing the simulated data, where "truth" represents parameter estimates from the actual magazine data. The problems caused by state-dependent covariates in the Chamberlain specification in column 2 are immediately evident. Focusing on the coefficient of the duration variable, $T_{i,t,\tilde{t}}$, we see that the estimate is severely skewed upwards; the true value is more than one standard deviation away. In column 3, the unconditional logit estimate for the coefficient on duration, on the other hand,

[10]It is important to note that due to the random draws, there is no serial correlation built into the fixed effect terms. One might think that the optimal pricing rules should be serially correlated over time – particularly since this is the basis for Cecchetti's assumption of fixed effects. Despite the randomness, the fixed effects will be correlated with the covariates due to the state dependence described earlier. If no correlation existed, then there would be no omitted variable bias. In the appendix, alternative models are created to examine the impact of serial correlation in the fixed effects.

[11]The parameters used as "truth" come from the replication of Cecchetti's estimation that will be discussed below.

[12]The size of the sample is chosen to correspond to the size of the magazine panel dataset.

is downward biased. This result matches the standard prediction that hazard slopes are downward biased when heterogeneity is not taken into account. Columns 4 and 5 present the Heckman-Singer estimates when the distribution representing the individual-specific effects contains two and three mass points respectively. The duration coefficient estimate for the specification with three mass points is very close to the true value. Estimates for the other coefficients, cumulative inflation and change in sales since the previous change, are more difficult to interpret because these variables are combinations of the lagged dependent variable and exogenous variables, whereas the duration variable is solely a function of the lagged dependent variable. The Heckman-Singer estimates in column 5 are reasonably close to the true values and the standard deviations of these simulation estimates are much smaller than for the conditional logit estimates. For the vast majority of the 10,000 samples, the addition of a fourth mass point did not lead to significant improvements in the likelihood function.

A second Monte Carlo experiment focuses on the interaction between the state-dependent covariates. Each covariate represents a cost or demand influence on the pricing decision, but these terms may often be collinear. For example, technology growth in this model is represented by the duration variable (T_{it}), indicating that technology is assumed to increase at a constant rate. Inflation is represented by cumulated inflation since last change (πT_{it}). In periods with relatively constant inflation, the model will not be able to distinguish between the two influences. This point is illustrated by constructing a dataset where the duration coefficient is set at 0. As before, 10,000 datasets were simulated, but this time "truth" was altered by setting the coefficient on $T_{i,t,\tilde{t}}$ equal to 0. The results are shown in Table 2.

By comparing "truth" in column 1 of Table 2 with the conditional logit estimates in column 2, it is readily apparent that the Chamberlain estimates suffer severely from state dependence. The problems from the first exercise are compounded by the inclusion of the duration variable $\left(T_{i,t,\tilde{t}}\right)$ when it has no impact on the model. Instead of obtaining an estimate of the duration coefficient near 0, the average estimate is 2.31 and the standard deviation of the 10,000 simulation estimates is 5.07. The unconditional logit estimates in column 3 suffer from the standard downward bias associated with ignoring the presence of heterogeneity. The Heckman-Singer point estimate for the duration coefficient matches truth precisely, and the coefficient estimates for $\pi_{i,t,\tilde{t}}$ and $\dot{Y}_{i,t,\tilde{t}}$ in column 5 appear to be slightly upward biased but well within the range of one standard deviation of the true parameters. We now examine these methods when applied to the magazine panel dataset.

4 Data

The magazine data represent the newsstand prices of thirty-eight magazines over the period 1953 to 1979.[13] The frequency of the data is annual, and a price change in a given year is defined as a change in the cover price between the first issue of the given year and the first issue of the following year. Inflation data is based upon the deflator for gross domestic non-farm produce, excluding housing services, from the Department of Commerce. Aggregate single copy sales data for the magazine industry were acquired by Cecchetti from the Magazine Publishers Association.

5 Results

In addition to replicating the estimates of Cecchetti and providing consistent estimates using the Heckman-Singer procedure, I perform two other estimations using alternative identification assumptions for the unobserved pricing rules. Each specification is based on the model presented by the combination of equations (5) and (6). First, the unconditional logit model is estimated, where the pricing rules are assumed to be the same for all firms and all periods in the sample. Next, a logit model with fixed-effects dummy variables is

[13] The list of magazines is located in the appendix of Cecchetti (1986).

estimated where the "individual" is defined as a magazine, rather than a three-year span within a magazine's history. Then, Chamberlain's fixed effects conditional logit procedure is used to replicate Cecchetti's results.[14] Finally, the Heckman-Singer estimates are presented. Results are reported in Table 3. The fixed-effects specification is denoted as (i = 3-year) for non-overlapping three-year groups and (i = mag.) for fixed effects at the magazine level.

The logit estimation results without fixed effects are in column 1. First, notice that the duration coefficient is negative, indicating that the probability of adjustment decreases as the time since the previous change increases. However, as mentioned before, a downward bias in the duration coefficient is expected in cases where heterogeneity has been ignored. This result is due to the fact that "individuals" who are very likely to change prices have done so in the first few years. The remaining "individuals," as time progresses, are those who are less likely to change prices. Failing to control for individual differences will cause the duration parameter to be biased downward because some individuals will be frequently changing prices after a year or two, over-representing the probability of a change in shorter durations compared to those who seldom change prices.

In column 2, fixed-effect dummy variables for individual magazines are added to the unconditional logit specification of column 1.[15] The coefficient estimate for duration is greater than the estimate in column 1, although it remains significantly negative. The coefficient for cumulative inflation since last change increases, while the coefficient on percentage change in sales falls. In comparing the first two models, the likelihood ratio statistic

[14]Cecchetti's results could not be precisely replicated due to the lack of price data for some magazines. His results are based upon a subsample of 954 observations. Since I do not have all of the data necessary to duplicate his subsample, which requires information on earlier price changes, the replication results are based upon the entire sample of 38 magazines for 27 years. Using Cecchetti's subsample criteria with the limited data omits 219 of the 1026 total observations and produces similar results.

[15]While using fixed-effect dummy variables to control for Cecchetti's assumed form of heterogeneity where $\bar{T} = 3$ would lead to severe bias in the estimates, the bias should be small for a model with magazine fixed effects where $\bar{T} = 27$.

indicates rejection of the restricted model in column 1 at the 5 percent level of significance in favor of the fixed-effects specification.[16] If heterogeneity in the data is best captured by differences across magazines, then duration appears to have a slight negative relationship with the probability of a price change.

The results from the conditional logit estimation are contained in column 3. The coefficient estimate for duration is 1.02, much greater than estimates from the other models and indicative of a time-dependent relationship with the probability of price adjustment. The estimates of the other coefficients are also much larger than those in columns 1 and 2. The inconsistency of the estimates due to state dependence precludes any significance testing.

The Heckman-Singer estimates in column 4 are similar to the estimates in the first two columns. As discussed above, the Heckman-Singer procedure calls for the gradual addition of supports (mass points) to the distribution, which are then estimated along with the probabilities. The reported results are based upon a model in which two mass points are used to represent the distribution of Cecchetti's assumed form of individual-specific effects. The addition of the second mass point resulted in only a marginal improvement of the likelihood function over the model in column 1, which is the model with a single mass point. Adding a third mass point resulted in no improvement of the likelihood function. This contrasts with the Monte Carlo estimation above where three distinct mass points were estimated and the other coefficient estimates were markedly different from the restricted logit model estimates.

Based upon the estimates from the Chamberlain conditional logit model, Cecchetti backs out a time series of average effects in the magazine industry. From this evidence, he argues that the movements in the effects are inconsistent with a constant real cost of price adjustment. A similar calculation cannot be computed from the Heckman-Singer

[16] The likelihood ratio statistic is 54.5 with 37 degrees of freedom. The 5 percent critical value for the chi-square distribution is 52.

estimates. The limitation of this model is that the effects are not estimated precisely. Even more problematic is the lack of significant improvement in the likelihood function over the logit model, which provides little support for Cecchetti's identification assumption in the first place.

There are several possible explanations for the Heckman-Singer estimation results. One concerns the issue of how the individual-specific effect terms, $a_{i,t,\tilde{t}}$, are generated. In the specification of the Heckman-Singer unconditional likelihood, I assume that the terms are randomly generated every 3 years. Despite the randomness, the variable will be correlated with the covariates because of the state dependence, but it may be more plausible to think that $a_{i,t,\tilde{t}}$ should be correlated across the three-year intervals for a given magazine. Incorporating the serial correlation into the Heckman-Singer specification, however, would lead to a very complicated likelihood function. Appendix A examines the Heckman-Singer model estimates under alternative data generating models.

An alternative approach is to assume that the optimal pricing rules are primarily functions of aggregate variables, such as inflation and money growth. This would imply that there would be fixed effects across magazines due to aggregate fluctuations, and these could be controlled through the introduction of time dummy variables. An additional explanation is that significant differences exist across magazines due to unobservable factors, such as managerial ability. Table 3 provides some evidence for the latter interpretation by comparing the likelihood values of the fixed effects logit model in column 2 to the unconditional logit model in column 1.

Combining these two hypotheses, Table 4 reports estimates of a fixed effects logit model which includes annual and magazine dummy variables. For comparison purposes, estimates from the restricted logit model in Table 3 are reproduced in column 1. Based upon the likelihood-ratio statistic, the restricted model in column 1 is rejected in favor of the model with fixed effects in column 2.[17] In comparison to the restricted model, two important

[17]The likelihood ratio statistic is 157.68 with 63 degrees of freedom. The 1 percent critical value for the

results emerge. First, the duration coefficient in now insignificantly different from zero, indicating that models based upon time-dependent price changes are not likely to closely fit the data. Second, the coefficient on cumulative inflation remains positive and statistically significant, providing support for state-dependent models.

6 Conclusion

Cecchetti's analysis is well motivated in its pursuit for empirical results documenting price stickiness in a particular industry. His selection of the magazine industry as the focus of analysis is arguably a good choice because of the fixed nature of magazine cover prices. The inconsistency of his estimates, however, nullifies the tests used to support his specification of heterogeneity. The Monte Carlo exercises illustrate the properties of estimates provided by the Heckman-Singer procedure, but when applied to the magazine data, this procedure does not identify significant heterogeneity at the three-year level. Other specifications provide some insight into the structure of heterogeneity. In particular, the estimates indicate support for heterogeneity at the magazine level. The use of annual dummy variables to capture the effects of aggregate variables also appears to be beneficial.

The corrected results confirm Cecchetti's finding that cumulative inflation is a primary factor in determining the probability of a price change. His conclusions on the behavior of the real cost of price adjustment and the effect of higher inflation on the frequency of adjustment, however, are dependent on his inconsistent estimation results. While the corrected estimates provide some information on the heterogeneity of magazines, this approach is not able to adequately control for the underlying pricing rules in a manner that permits inference on the structure of price adjustment costs.

An alternative approach would be to directly specify a structural dynamic-programming

relevant chi-square distribution is 92.01.

model for a firm in this industry.[18] A structural model will permit direct analysis of variously specified sources of heterogeneity and idiosyncratic differences across firms. More importantly, this type of analysis allows for direct estimates of the magnitude of price adjustment costs.

[18] See Willis (2000).

References

Aguirregabiria, Victor, "The Dynamics of Markups and Inventories in Retailing Firms," *Review of Economics Studies*, April 1999, *66* (2), 275–308.

Ball, Laurence and David Romer, "Real Rigidities and the Non-Neutrality of Money," *The Review of Economic Studies*, April 1990, *57* (2), 183–204.

Blanchard, Olivier and Nobuhiro Kiyotaki, "Monopolistic Competition and the Effects of Aggregate Demand," *American Economic Review*, September 1987, *77*, 647–666.

Card, Daniel and Daniel Sullivan, "Measuring the Effect of Subsidized Training Programs on Movements In and Out of Employment," *Econometrica*, May 1988, *56*, 497–530.

Cecchetti, Stephen, "The Frequency of Price Adjustment: A Study of the Newsstand Prices of Magazines," *Journal of Econometrics*, August 1986, *31*, 255–274.

Chamberlain, Gary, "Analysis of Covariance with Qualitative Data," *Review of Economic Studies*, 1980, *47*, 225–238.

—— , "Heterogeneity, Omitted Variable Bias, and Duration Dependence," *Longitudinal Analysis of Labor Market Data*, James Heckman and Burton Singer, eds. Cambridge University Press: Cambridge, UK 1985.

Greene, William, *Econometric Analysis*, Macmillan: New York 1999.

Heckman, James and Burton Singer, "The Identification Problem in Econometric Models for Duration Data," *Advances in Econometrics*, Cambridge University Press: Cambridge, UK 1982.

—— **and** —— , “A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data,” *Econometrica*, March 1984, *52* (2), 271–320.

Iwai, Katsuhito, *Disequilibrium Dynamics*, Yale University Press: New Haven, CT 1981.

Lancaster, Tony, *The Econometric Analysis of Transition Data*, Cambridge University Press: Cambridge, UK 1990.

Lindsay, Bruce, “The Geometry of Mixture Likelihoods, Part I,” *Annals of Statistics*, 1983a, *11*, 86–94.

—— , “The Geometry of Mixture Likelihoods, Part II,” *Annals of Statistics*, 1983b, *11*, 783–792.

Sheshinski, Eytan and Yoram Weiss, “Inflation and Costs of Price Adjustment,” *Review of Economics Studies*, 1977, *44*, 281–303.

—— **and** —— , “Optimal Pricing Policy Under Stochastic Inflation,” *Review of Economics Studies*, 1983, *51*, 281–303.

Slade, Margaret, “Optimal Pricing with Costly Adjustment: Evidence from Retail-Grocery Prices,” *Review of Economic Studies*, January 1998, *65*, 87–107.

Trussell, James and Toni Richards, “Correcting for Unmeasured Heterogeneity in Hazard Models: An Application of the Heckman-Singer Strategy to Demographic Data,” *Sociological Methodology*, 1985, pp. 242–276.

Willis, Jonathan, “Estimation of Adjustment Costs in a Model of State-Dependent Pricing,” Federal Reserve Bank of Kansas City Research Paper No. 00-07, December 2000.

Appendix A

In the Monte Carlo exercises presented in the paper, the Heckman-Singer model produced estimates that were very close to the parameters of the data generating model. The data generating model, however, contained an assumption on the stochastic nature of the individual-specific effect that may not be true for the magazine industry. This section examines the robustness of the Heckman-Singer estimates for alternative assumptions on the individual-specific effect.

Recall that the individual-specific effect in this application is a proxy for the firm's optimal pricing rules. These pricing rules should be inherently correlated with the state variables of the firm's optimization problem, such as the rate of inflation and an indicator of industry demand. Serial correlation in these state variables would likely lead to serial correlation in the pricing rules. Cecchetti assumes that the serial correlation is very large and the innovations are very small, so that the firm's optimal pricing rules can be approximated by rules that are fixed for non-overlapping 3-year periods.

In the data generating model used for the Monte Carlo exercises, the individual-specific effect was assumed to be drawn randomly from a uniform distribution. This assumption conforms closely with the likelihood function of the Heckman-Singer model, which uses a mass point distribution to represent random effects. If the individual-specific effects are generated under an alterative assumption, it is unclear how the Heckman-Singer model will perform.

To investigate the properties of the Heckman-Singer model, additional Monte Carlo exercises were undertaken. Instead of using a uniform distribution, the individual-specific effects are assumed to follow an autoregressive process of the form

$$a_{i,g} = \mu + \rho a_{i,g-1} + \varepsilon_{i,g} \tag{8}$$

where $a_{i,g}$ is the effect for firm i over the 3-year interval g and $\varepsilon_{i,g}$ is a Gaussian innovation to the process with mean 0 and standard deviation σ_ε. In other words, there will be 9 individual-specific 3-year effects created from the autoregressive process for the sample of 27 periods for each firm. The effects are assumed to be independent across firms.

Table A1 presents the results of Monte Carlo exercises when the individual-specific effects within a firm are generated by this autoregressive process. The exercise is repeated for five different values of the persistence parameter, $\rho \in \{0, 0.3, 0.6, 0.9, 0.99\}$. The other parameters, $\{\mu, \sigma_\varepsilon\}$, are specified such that the mean of the process is -5 and the standard deviation is 1. As expected, the Chamberlain conditional logit estimates fair poorly in all cases due to the presence of state-dependent covariates. The logit estimates in column 3 are downward biased due to the omitted variable problem, and the bias becomes slightly worse for the duration and cumulative inflation coefficients as the persistence of the individual-specific effect increases. The estimates from the Heckman-Singer model with 3 mass points are closest to the true parameters. All three coefficient estimates decrease as persistence increases, but the change in minimal. Interestingly, as the persistence increases, the fraction of simulations in which the introduction of a fourth mass point would provide any additional improvement in the likelihood decreases. Despite the misspecification of the likelihood function in this case, the Heckman-Singer model still performs well.

Table A2 provides results of Monte Carlo exercises where there is no time dependence in the data generating model. The results are qualitatively similar to Table A1, with the exception that the Chamberlain conditional logit estimates are much more volatile.

One final robustness exercise would be to examine the Heckman-Singer estimates when the individual-specific effects are correlated with aggregate inflation and industry demand variables in the data generating model. In such a circumstance, it would be much more effective to solve directly for the firm's policy functions with a structural model than to use an assumption of policy rules that are fixed for 3-year intervals.

Table 1: Monte Carlo Exercise Based Upon Cecchetti's Parameter Estimates

	(1) Truth	(2) Chamberlain Cond. Logit	(3) Logit	(4) Heckman-Singer (2 mass points)	(5) Heckman-Singer (3 mass points)
$T_{i,t,\tilde{t}}$	1.02	2.86	0.49	0.89	0.98
		(1.20)	(0.06)	(0.15)	(0.19)
$\pi_{i,t,\tilde{t}}$	19.20	19.93	11.51	17.31	18.61
		(13.19)	(1.51)	(2.85)	(3.36)
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.34	4.90	6.88	7.35
		(5.00)	(1.12)	(1.67)	(1.88)

NOTE: The numbers reported in parentheses are standard deviations of the estimates across the 10,000 simulations. Estimates of the constant for the logit model and the mass points for the Heckman-Singer specification are not displayed.

Table 2: Monte Carlo Exercise with No Time Dependence

	(1) Truth	(2) Chamberlain Cond. Logit	(3) Logit	(4) Heckman-Singer (2 mass points)	(5) Heckman-Singer (3 mass points)
$T_{i,t,\tilde{t}}$	0	2.31	-0.02	0.00	0.00
		(5.07)	(0.03)	(0.05)	(0.05)
$\pi_{i,t,\tilde{t}}$	19.20	29.83	11.26	18.00	19.92
		(39.37)	(1.28)	(2.83)	(3.89)
$\dot{Y}_{i,t,\tilde{t}}$	7.60	6.26	5.10	7.25	7.84
		(11.10)	(1.13)	(1.71)	(1.99)

NOTE: The numbers reported in parentheses are standard deviations of the estimates across the 10,000 simulations. Estimates of the constant for the logit model and the mass points for the Heckman-Singer specification are not displayed.

Table 3: Coefficient Estimates for Magazine Price Model

	(1) Logit	(2) Fixed-effects Logit i = mag.	(3) Chamberlain Cond. Logit i = 3-year	(4) Heckman-Singer i = 3-year	
$T_{i,t,\tilde{t}}$	-0.10	-0.07	1.02	-0.09	
	(0.03)	(0.03)	(0.28)	(0.04)	
$\pi_{i,t,\tilde{t}}$	6.93	8.83	19.20	8.23	
	(1.12)	(1.25)	(7.51)	(1.53)	
$\dot{Y}_{i,t,\tilde{t}}$	-0.36	-1.14	7.60	-0.13	
	(0.98)	(1.06)	(3.46)	(1.14)	
Constant	-1.90				
	(0.14)				
Mass point 1				-1.94	[0.88]
				(0.20)	[(0.16)]
Mass point 2				-29.15	[0.12]
				(1.1e+11)	[(0.16)]
Log like.	-500.45	-473.18	-83.72	-499.65	
Obs.	1026	1026	1026	1026	

NOTE: The numbers in parentheses are standard errors, but estimates using Chamberlain's method are inconsistent as described above. The formulation used for specifying "individuals" in fixed-effects estimations (choosing i) is stated at the top of each column. Column 1 reports unconditional logit estimates. Column 2 reports unconditional logit estimates with fixed-effects dummy variables. Coefficient estimates for the dummy variables are not reported. Column 3 reports results from the Chamberlain conditional logit estimation. Column 4 contains results from Heckman-Singer procedure where two mass points are estimated to capture the individual-specific effects. The probabilities associated with each mass point are listed in square brackets.

Table 4: Coefficient Estimates when Jointly Controlling for Magazine and Year Effects

	(1) Logit	(2) Logit with Fixed Effects
$T_{i,t,\tilde{t}}$	-0.10	0.07
	(0.03)	(0.07)
$\pi_{i,t,\tilde{t}}$	6.93	5.84
	(1.12)	(2.25)
$\dot{Y}_{i,t,\tilde{t}}$	-0.36	-1.51
	(0.98)	(2.23)
Constant	-1.90	
	(0.14)	
Log like.	-500.45	-421.61
Obs.	1026	1026

NOTE: The numbers in parentheses are standard errors. Estimates presented in column 2 are from a fixed-effects unconditional logit specification which included yearly dummy variables and magazine dummy variables. The coefficient estimates for the dummy variables are jointly significant and are omitted from the table due to space considerations.

Table A1: Alternative Monte Carlo Exercises Based Upon Cecchetti's Parameter Estimates

	(1) Truth	(2) Chamberlain Cond. Logit	(3) Logit	(4) Heckman-Singer (2 mass points)	(5) Heckman-Singer (3 mass points)	
$T_{i,t,\tilde{t}}$	1.02	3.18	0.78	0.86	0.99	
		(1.65)	(0.07)	(0.16)	(0.18)	
$\pi_{i,t,\tilde{t}}$	19.20	14.45	15.77	16.96	18.85	$\rho = 0$
		(13.29)	(1.72)	(2.36)	(2.91)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.32	6.33	6.61	7.41	
		(5.47)	(1.20)	(1.66)	(1.70)	
$T_{i,t,\tilde{t}}$	1.02	3.19	0.77	0.84	0.97	
		(1.41)	(0.08)	(0.15)	(0.18)	
$\pi_{i,t,\tilde{t}}$	19.20	14.13	15.72	16.84	18.64	$\rho = 0.3$
		(12.99)	(1.78)	(2.37)	(2.94)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.33	6.34	6.59	7.37	
		(5.36)	(1.21)	(1.67)	(1.70)	
$T_{i,t,\tilde{t}}$	1.02	3.20	0.76	0.82	0.95	
		(1.60)	(0.08)	(0.15)	(0.17)	
$\pi_{i,t,\tilde{t}}$	19.20	13.91	15.68	16.69	18.41	$\rho = 0.6$
		(12.87)	(1.82)	(2.33)	(2.89)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.34	6.34	6.54	7.31	
		(5.36)	(1.19)	(1.62)	(1.63)	
$T_{i,t,\tilde{t}}$	1.02	3.17	0.75	0.82	0.93	
		(1.08)	(0.08)	(0.14)	(0.17)	
$\pi_{i,t,\tilde{t}}$	19.20	13.84	15.66	16.65	18.22	$\rho = 0.9$
		(12.68)	(1.74)	(2.25)	(2.74)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.42	6.34	6.55	7.26	
		(5.30)	(1.13)	(1.54)	(1.56)	
$T_{i,t,\tilde{t}}$	1.02	3.20	0.75	0.82	0.93	
		(1.75)	(0.09)	(0.14)	(0.17)	
$\pi_{i,t,\tilde{t}}$	19.20	13.82	15.65	16.65	18.23	$\rho = 0.99$
		(13.06)	(1.66)	(2.17)	(2.70)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.43	6.35	6.56	7.27	
		(5.45)	(1.10)	(1.52)	(1.55)	

NOTE: The numbers reported in parentheses are standard deviations of the estimates across the 10,000 simulations.

Table A2: Alternative Monte Carlo Exercises with No Time Dependence

	(1) Truth	(2) Chamberlain Cond. Logit	(3) Logit	(4) Heckman-Singer (2 mass points)	(5) Heckman-Singer (3 mass points)	
$T_{i,t,\tilde{t}}$	0	6.05	-0.01	0.00	0.00	
		(16.66)	(0.03)	(0.04)	(0.04)	
$\pi_{i,t,\tilde{t}}$	19.20	31.03	15.70	18.59	20.47	$\rho = 0$
		(160.02)	(1.50)	(3.14)	(3.90)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	8.72	6.50	7.34	7.99	
		(88.15)	(1.25)	(1.58)	(1.83)	
$T_{i,t,\tilde{t}}$	0	6.10	-0.02	-0.01	-0.01	
		(16.89)	(0.03)	(0.04)	(0.04)	
$\pi_{i,t,\tilde{t}}$	19.20	25.93	15.50	18.12	19.78	$\rho = 0.3$
		(143.93)	(1.53)	(3.10)	(3.79)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	9.52	6.38	7.12	7.71	
		(89.82)	(1.24)	(1.54)	(1.80)	
$T_{i,t,\tilde{t}}$	0	6.40	-0.03	-0.02	-0.02	
		(18.92)	(0.03)	(0.03)	(0.04)	
$\pi_{i,t,\tilde{t}}$	19.20	24.97	15.31	17.61	19.10	$\rho = 0.6$
		(143.52)	(1.54)	(2.99)	(3.98)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	15.81	6.28	6.95	7.45	
		(104.68)	(1.17)	(1.46)	(1.73)	
$T_{i,t,\tilde{t}}$	0	7.10	-0.04	-0.03	-0.03	
		(21.58)	(0.03)	(0.03)	(0.04)	
$\pi_{i,t,\tilde{t}}$	19.20	17.05	15.12	17.20	18.46	$\rho = 0.9$
		(107.99)	(1.56)	(3.07)	(3.86)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	14.38	6.17	6.75	7.19	
		(98.23)	(1.20)	(1.45)	(1.67)	
$T_{i,t,\tilde{t}}$	0	7.64	-0.04	-0.04	-0.04	
		(25.01)	(0.03)	(0.03)	(0.03)	
$\pi_{i,t,\tilde{t}}$	19.20	16.67	15.06	16.98	18.19	$\rho = 0.99$
		(156.08)	(1.59)	(2.97)	(3.59)	
$\dot{Y}_{i,t,\tilde{t}}$	7.60	15.40	6.08	6.58	7.02	
		(97.87)	(1.15)	(1.42)	(1.63)	

NOTE: The numbers reported in parentheses are standard deviations of the estimates across the 10,000 simulations.