Cost Pass-Through in Estimation

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Abstract

Recent literature has made explicit the relationship between cost pass-through rates and the functional form of demand. Though empirical cost pass-through rates have been estimated, there has been little effort to estimate cost pass-through rates in a manner consistent with a specified demand system. In this paper, we show that, in general, cost pass-through cannot be consistently estimated by a reduced-form regression. We identify three sources of bias that provide a theoretical motivation for our analysis. Using a numerical simulation, we show how prediction error varies across demand systems and regression specifications. We provide heuristic suggestions for how to improve estimation accuracy for pass-through rates in different settings.

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1 Introduction

This paper addresses whether cost pass-through can be accurately estimated from reduced form regressions of prices on costs. Cost pass-through measures how firms transmit cost shocks to consumers via prices. As such, the extent of cost pass-through has important implications for any policy or market change where costs are affected. Macroeconomists have studied the effect of cost pass-through on inflation, optimal monetary policy, and the evolution of unemployment. There is a rich international trade literature on cost shocks induced by exchange rate fluctuations, which emphasizes the presence of incomplete pass-through and its implications for consumer prices and trade flows. In industrial organization, cost pass-through plays an important role in understanding firm responses to events like shifts in government regulations or mergers. Furthermore, recent industrial organization research uses cost pass-through to infer structural demand parameters when demand estimation is infeasible (Miller, Remer, and Sheu (2013)) and to evaluate counterfactual scenarios while relaxing structural assumptions (Miller, Remer, Ryan, and Sheu (2012) and Jaffe and Weyl (2013)).

These implications have in turn motivated a growing body of empirical research based on reduced-form regressions of prices on costs. Although this literature is too large to fully summarize here, recent examples include examinations of incomplete cost pass-through (e.g., Nakamura and Zerom (2010), Golberg and Hellerstein (2011), Atkin and Donaldson (2012)), the retail and wholesale components of cost pass-through (e.g., Nakamura (2008), Gopinath, Gourinchas, Hsieh, and Li (2011)), how cost-pass through is affected by horizontal market structures (e.g., Atkeson and Burstein (2008), Berman, Martin, and Mayer (2011), Auer and Schoenle (2012), Hong and Li (2013)) and vertical market structures (e.g., Hellerstein and Villas-Boas (2010), Neiman (2010), Neiman (2011), Hong and Li (2013)), and the sources of asymmetric cost pass-through (e.g., Borenstein, Cameron, and Gilbert (1997), Peltzman (2000)).

Given the wide-ranging applications of cost pass-through, a key question is whether it can be empirically quantified. Although the standard reduced form regressions may be sufficient for the purposes of establishing a correlation in the data, they are difficult to interpret structurally for the purposes of out-of-sample predictions or for guiding modeling decisions. Our objective is to develop results, leveraging oligopoly price theory, that are useful in interpreting these existing pass-through estimates and in designing future regression specifications.

This paper distinguishes three types of cost pass-through: *own pass-through*, which is how a firm's prices adjust in response to changes in its costs; *cross pass-through*, which is how a firm's prices adjust in response to changes in its competitors' costs, and *industry pass-through*, which is how a firm's prices adjust in response to changes in costs industry-wide. It has been understood since at least Bulow and Pfleiderer (1983) that these pass-through rates, in equilibrium, are tightly linked to consumer demand schedules and in particular to demand curvature. Furthermore, these issues have found renewed emphasis in Fabinger and Weyl (2012) and Weyl and Fabinger (2012). Demand curvature determines how elasticities (and thus optimal markups) change as prices move away from an equilibrium. As a general rule, pass-through need not be constant and instead can vary depending on the costs faced by firms.

We show that standard oligopoly theory has nuanced but potentially serious ramifications for the interpretation of reduced-form estimates. Three sources of bias can arise. The first is *misspecification bias* caused by the non-linear relationship between equilibrium prices and quantities in the data generating process. This results in nonconstant pass-through, in which case linear regression coefficients may not characterize pass-through at *any* given level of costs or prices, including at the average level. The second bias, which we refer to as *partial information bias*, is also caused by nonconstant pass-through and can arise when researchers regress prices on partial measures of cost (i.e., "cost shifters"). This can create correlations between the regressors and the error term even if the observed and unobserved portions of cost are uncorrelated. Finally, a third bias can arise when researchers regress a firm's prices on its costs without accounting for the costs of the firm's competitors. We refer to this as *missing variables bias*. Whether the resulting regression coefficient is closer to own pass-through or industry pass-through depends on the degree of correlation between firms' costs and on the curvature of demand, which affects the strategic complementarity of prices.

Using Monte Carlo experiments, we then characterize the likely empirical significance of these complications in a number of relevant settings. Oligopoly theory indicates that the magnitude and constancy of equilibrium pass-through, as well as the strategic complementarity of prices, depend on consumer demand schedules. Therefore, in the data generating process we feature five different demand functions that commonly appear in the literature: multinomial logit demand, mixed logit demand, the almost ideal demand system (AIDS) of Deaton and Muellbauer (1980), linear demand, and log-linear (or "isoelastic") demand. For each demand system, we calibrate a range of demand parameters that reflects different industry conditions, margins and product substitutability in an initial equilibrium. Hereafter we refer to a given calibrated demand system as an "industry." We recompute equilibrium in each industry for each of many different marginal cost vectors, drawn stochastically, and obtain the prices and theoretical pass-through rates that arise at each realization of costs.

In turn, we then regress prices on costs, separately for each industry, and compare the obtained regression coefficients with the true theoretical pass-through rates that arise in equilibrium. We consider three main reduced-form specifications: (i) regressions of a firm's prices on its costs and the costs of competitors, alternately with fully and partially observed costs; (ii) regressions of a firm's prices on its costs, omitting the costs of competitors, again alternately with fully and partially observed costs; and (iii) regressions of a firm's prices on a measure of industry-wide costs. We characterize the magnitude of bias that arises under different conditions and develop the extent to which accounting for nonlinearities in the reduced-form regression specification reduces bias in the regression coefficients.

[This is where a summary of findings goes]

We believe this paper is the first to explore the implications of oligopoly price theory on reduced form estimation of cost pass-through. In developing results, we employ data generating processes that incorporate many different functional forms for demand and a wide-ranging set of market conditions. However, we have made simplifications along other fronts. Perhaps most importantly, the Monte Carlo experiments incorporate firms that (i) have full knowledge of their consumer demand schedules and (ii) adjust prices seamlessly in response to changing industry conditions. Our results do not necessarily apply to settings in which firms use constant markups or other rules of thumb to set prices, or to settings in which market frictions such as menu costs create discontinuities in the price-cost relationship. We also have set aside complications arising from the vertical structure of the supply chain. Our results are generated using the Nash-Bertrand equilibrium concept, though we suspect that they extend at least qualitatively to consistent conjectures and other notions of equilibrium. Many of the above considerations may affect the reliability of reduced-form estimation, and we are optimistic that they can be explored more fully in subsequent research.

The paper proceeds as follows. Section 2 develops an oligopoly theory of cost pass-through, highlights the linkages between pass-through and demand, and discusses the implications of the theory for reduced-form estimates of prices on costs. Section 3 details the construction of the Monte Carlo experiments, focusing in particular on the parameterizations of the employed demand functions and the cost draws at which equilibrium is computed. Section 4 evaluates the Monte Carlo experiments, while Section 5 provides recommendations for researchers wishing to estimate cost pass-through. Section 6 concludes.

2 Motivation and Framework

2.1 An oligopoly theory of cost pass-through

We start by developing the theoretical relationship between costs and prices, which we then use to inform the interpretation of reduced form regressions. Throughout we focus on models of Bertrand-Nash competition in which firms face well-behaved and twice-differentiable demand functions.[1]

Let each firm i produce some subset of the products available to consumers, setting prices to maximize short-run profits and taking as given the prices of competitors. The first order conditions that characterize firm i's profit-maximizing prices can be expressed as

$$f_i(P;\theta) \equiv -\left[\frac{\partial Q_i(P;\theta)}{\partial P_i}^T\right]^{-1} Q_i(P;\theta) - (P_i - MC_i(P;\theta)) = 0, \tag{2.1}$$

where Q_i is a vector of firm i's unit sales, P_i is a vector of firm i's prices, P is a vector of all prices, and MC_i is a vector of firm i's marginal cost. Both sales and marginal costs are modeled as functions of all prices and the underlying structural parameters.

Jaffe and Weyl (2013) show that these first order conditions can be used to obtain an expression for cost pass-through. Suppose that a per-unit tax t is levied on each product in the model. The post-tax first order conditions are

$$f(P;\theta) + t = 0,$$

where t is the vector of taxes and $f(P;\theta) = [f_1(P;\theta)' \; f_2(P;\theta)' \; \ldots]'$. Differentiating with respect to t obtains

$$\frac{\partial P}{\partial t}\frac{\partial f(P;\theta)}{\partial P} + I = 0,$$

and algebraic manipulations then yield the cost pass-through matrix:

$$\rho(P;\theta) \equiv \frac{\partial P}{\partial t} = -\left(\frac{\partial f(P;\theta)}{\partial P}\right)^{-1}. \tag{2.2}$$

[1] The calculations in this section generalize to other equilibria concepts, including Cournot-Nash and consistent conjectures, provided that there is a single strategic variable per product.

According to this expression, cost pass-through equals the opposite inverse of the Jacobian of $f(P;\theta)$ and, as such, it depends on both the first derivatives of demand (i.e., the demand elasticities) and the second derivatives of demand (i.e., the demand curvature). Pass-through depends on demand curvature since curvature determines how elasticities, and thus optimal markups, change as prices move away from an equilibrium.

The diagonal elements of the cost pass-through matrix, which we refer to as *own pass-through*, characterize how firms adjust the prices of a product in response to changes in that product's costs. The off-diagonal elements, which we refer to as *cross pass-through*, characterize how firms adjust the prices of a product in response to changes in the costs of other products. Cross pass-through is closely related to the concept of strategic complementarity, as introduced in Bulow, Geanakoplos, and Klemperer (1985).[2] Higher levels of strategic complementarity correspond to greater cost pass-through. This relationship exists because the first order condition characterizing the profit-maximizing price of a product, as expressed in equation (2.1), depends on other products' costs only insofar as they affect prices.

The pass-through matrix in equation (2.2) dictates how prices adjust to product-specific cost perturbations. Also of empirical and theoretical interest is *industry pass-through*, or how prices adjust to industry-wide cost shocks affecting all products equally. We characterize industry pass-through as a vector where the j^{th} element characterizes the price response of product j to an industry-wide cost shock. This element equals

$$\rho_j^I(P;\theta) = \sum_k \rho_{jk}(P;\theta), \tag{2.3}$$

where ρ_{jk} is the entry in the j^{th} row and k^{th} column of the cost pass-through matrix. Industry cost pass-through also depends on both demand elasticities and demand curvature.

2.2 Cost pass-through and the form of demand

Recent theoretical research emphasizes the connection between cost pass-through and demand curvature (e.g., Weyl and Fabinger (2012)). Among the demand systems commonly used by economists, demand curvature and pass-through are determined either completely or nearly completely by the system's price elasticities (Fabinger and Weyl (2012)). Furthermore, the form of these elasticities varies markedly across demand functional forms. It follows that studying how the reliability of reduced-form estimation is affected by demand curvature depends on which demand form one takes as the "truth." Therefore, here we examine multiple demand systems.

In our Monte Carlo experiments, we consider five specific demand systems: linear, log-linear, multinomial logit, mixed logit, and almost ideal. Among these, the first two belong to a class of demand functions identified by Bulow and Pfleiderer (1983) as having constant cost pass-through. Therefore, the bias due to incorrectly assuming a linear pass-through rate does not arise when demand is believed to be linear or log-linear. Functions in this class are most common in theoretical work and in empirical models of homogeneous product oligopolies. Both logit and mixed logit belong to a class of discrete-choice demand functions that typically

[2] Indeed, strategic complementarity is defined in Bulow, Geanakoplos, and Klemperer (1985) based on the off-diagonal elements of a matrix analogous to $\partial f(P;\theta)/\partial P$.

are employed in empirical models of differentiated products (e.g., Berry, Levinsohn, and Pakes (1995) and Nevo (2001)). The AIDS similarly is used in many empirical applications (e.g., Hausman 1997). Fabinger and Weyl (2012) show that cost pass-through is not constant in prices for these latter demand systems.

As an example of how pass-through can vary by functional form, take a stark comparison: the linear demand system and the (highly convex) log-linear demand system. These two demand systems have the forms

$$q_i = \alpha_i + \sum_j \beta_{ij} p_j, \qquad \text{and} \qquad \ln(q_i) = \gamma_i + \sum_j \epsilon_{ij} \ln p_j, \tag{2.4}$$

respectively. Miller, Remer, and Sheu (2013) show that the elements of the Jacobian of $f(P)$ are

$$\frac{\partial f_i(P)}{\partial p_j} = \begin{cases} -2 & \text{if } i = j \\ -\beta_{ij}/\beta_{ii} & \text{otherwise.} \end{cases} \tag{2.5}$$

with linear demand and

$$\frac{\partial f_i(P)}{\partial p_j} = \begin{cases} -\frac{1+\epsilon_{ii}}{\epsilon_{ii}} & \text{if } i = j \\ 0 & \text{otherwise.} \end{cases} \tag{2.6}$$

with log-linear demand. Inverting the Jacobian reveals that while the own pass-through rates that arise with linear demand typically are bounded below by 0.5, the own pass-through rates that arise with log-linear demand are bounded below by unity. In contrast, cross pass-through with linear demand is positive when the goods are substitutes, while cross pass-through with log-linear demand is zero. Therefore, the performance of reduced-form regressions for pass-through depends on the convexity of the underlying consumer demand schedule.

2.3 Implications for reduced form regression analysis

Consider a regression equation aimed at recovering the full cost pass-through matrix, including all cross terms:

$$p_{jt} = a + \sum_{k=1}^{J} b_{jk} c_{kt} + e_{jt}, \tag{2.7}$$

where p_{kt} and c_{kt} are the price and cost of product k at time t and e_{kt} is an error term. This linear estimating equation is seen in the empirical pass-through literature.[3] Usually one would like to interpret the resulting own-cost coefficient estimates, $\widehat{b}_{jj}\ \forall j$, as own pass-through rates and the resulting cross-cost coefficient estimates, $\widehat{b}_{jk}\ \forall j \neq k$, as cross pass-through rates. Similarly, researchers might want to use $\sum_k \widehat{b}_{jk}$ to estimate the industry pass-through rate.

For a number of applications, equation (2.7) is simplified in order to accommodate data availability constraints. Although equation (2.7) has the potential to recover to the full cost pass-through matrix, in practice the cost pass-through terms are often difficult to identify

[3] Take for example Besanko, Dube, and Gupta (2005).

given the variation that is seen in typical data sets. As a result, researchers frequently modify the specification to include only a single firm-specific cost regressor, i.e.,

$$p_{jt} = a^F + b_j^F c_{jt} + e_{jt}^F, \tag{2.8}$$

which regresses the prices of each product on its costs, but not the costs of other goods. In other papers, only aggregate cost shocks are observed, resulting in equations like

$$p_{jt} = a^I + b_j^I c_t^I + e_{jt}^I, \tag{2.9}$$

which regresses prices on an industry-wide cost shifter such as a commodity price or exchange rate index. Usually one would like to use $\widehat{b_j^F}$ as an estimate of own cost pass-through and $\widehat{b_j^I}$ as an estimate of industry pass-through.

However, the oligopoly theory developed in the previous sections suggests difficulties in using the regression coefficients from these equations as pass-through rates. The first issue is due to functional form misspecification: the linear regression equation is at odds with the data generating process except in the specific case where consumers behave according to a constant pass-through demand system. What the regression obtains (assuming for the moment that costs are uncorrelated with the error term) is an unbiased estimate of the average effect of costs on prices observed in the data. If true cost pass-through is not constant, this may not characterize pass-through at *any* given level of costs or prices, including at the average level.[4] Therefore it is difficult to use the resulting estimates to generate counterfactuals or to motivate the structure of a proposed theoretical model.

A second difficulty arises when the econometrician observes costs only partially, and not total costs. This situation is quite common, as firms do not wish to disclose the proprietary details of their costs to competitors, meaning that the econometrician frequently only sees certain cost components. The unobserved portion of costs then is in the error term. *With nonlinear cost pass-through, this can create bias even if the observed and unobserved portions of costs are uncorrelated.* The reason is that the impact of unobserved costs on prices depends on the level of observed costs via the structure of the demand system. This in turn induces a correlation between the regressors and the error term. For instance, if cost pass-through decreases with costs then a negative correlation between the regressor and the error term would arise, leading the regression coefficients to be biased downwards, even if one only wants to measure the average effect of observed costs on prices.[5] This second difficulty is, of course, exacerbated if observed costs are correlated with unobserved costs.

For equations (2.8) and (2.9) an additional difficulty arises because of omitted variable bias. To illustrate, consider first equation (2.8) and assume, for simplicity, that the data generating process features constant cost pass-through. Then $\widehat{b_j^F}$ is biased upward if the costs of

[4]For example, if the true relationship expressing price as a function of cost is everywhere strictly concave, the coefficient $\widehat{b}_{11}$ from equation (2.7) will only equal pass-through at average cost $\overline{c_1}$ if the coefficient just happens to equal the slope of the true relationship at $\overline{c_1}$. This is highly unlikely for a generic data set of price observations at different realized costs.

[5]To take a formal example, write the relationship between prices and costs in a one product demand system as $p_{jt} = b(c_{jt})c_{jt}$. Here the extent of pass-through depends on the values of costs c_{jt}. Assume that costs are composed of two components, one observed by the econometrician and one unobserved, giving $c_{jt} = c_{jt}^o + c_{jt}^u$. Imagine running a regression of the form $p_{jt} = bc_{jt}^o + e_{jt}$, with the aim of estimating the average effect of observed costs on prices. Then $b(c_{jt})c_{jt}^u$ enters into the regression error, and due to the presence of $b(c_{jt})$ we expect this term to be correlated with c_{jt}^o.

substitute products are positively correlated, as one might expect them to be. Whether the coefficient is closer to own cost pass-through (less bias) or closer to industry pass-through (more bias) depends both on the degree of correlation between the costs of firms and on the curvature of the consumer demand schedule. The correct interpretation of the regression coefficient therefore depends on two economic considerations about which the econometrician may have little information. The regression coefficient in equation (2.9) is likely less vulnerable to this source of bias, because industry-wide cost shifters can often be found that are plausibly uncorrelated with firm-specific costs.

3 Research methodology

3.1 Overview of the numerical exercise

Our objective is to develop results, leveraging the oligopoly price theory, that are useful to economists in interpreting published pass-through estimates and in designing regression specifications for future research. To that end, we use Monte Carlo experiments to ascertain the empirical significance of the econometric difficulties discussed in the previous section. The generated data track how firms in an industry, defined as a specific parameterization of a joint demand system and cost process, adjust prices in response to different cost realizations. Then we regress these prices on costs, separately for each industry, and compare the obtained regression coefficients to the theoretical pass-through rates produced by the model that generated the data.

The data generating process has three distinct steps. First, we build a set of "industries," where each industry is defined by a specific parameterization of one of the five demand systems and a cost process specification. The demand sytems considered are logit, almost ideal, linear, log-linear and mixed logit. The cost process follows one of eight specifications, which vary in the proportion of costs that are observed by the econometrician and the correlation between unobserved costs. Second, we draw stochastically a large number of cost vectors, where each vector contains a cost entry for each product in the demand system. Third, we compute the Bertrand-Nash equilibrium for each industry and cost vector combination, deriving theoretical cost pass-through, following equation (2.2), at the equilibrium prices. Finally, we run reduced-form regressions of price on cost by industry, emulating an econometrician attempting to estiamate passthrough with price and cost data. This enables us to compare the theoretical cost pass-through rates to empirical estimates obtained with various industry-specific reduced-form regressions.

For this paper, we limit our simulations to two-good industries. Eachindustry includes two single-product firms. For the relevant demand systems (logit, AIDS, and mixed logit), there is a fixed-price outside option that is standard in the literature.. By limiting the number of strategic firms, we avoid the curse of dimensionality in the reduced-form regressions, since the number of pass-through rates to be estimated increases with the square of the number of products. Given the structure of the demand systems, we see no reason to think that our results would not generalize to industries with more than two firms, provided sufficient cost variation is available to separately identify the pass-through rates.

3.2 Details on the demand functional forms

We turn now to the mathematics of the selected demand systems. The first is the logit demand system, which takes the form

$$s_i = \frac{e^{(\eta_i - \tau p_i)}}{\sum_k e^{(\eta_k - \tau p_k)}}, \tag{3.1}$$

where s_i is the market share of product i (i.e. $s_i = q_i/M$ for market size M).

The AIDS of Deaton and Muellbauer (1980) is written as

$$w_i = \psi_i + \sum_j \phi_{ij} \log p_j + \theta_i \log(X/P^*), \tag{3.2}$$

where w_i is the expenditure share for product i (i.e., $w_i = p_i q_i / \sum_k p_k q_k$), X is the total expenditure across all products, and P^* is a price index given by

$$\log(P^*) = \psi_0 + \sum_k \psi_k \log(p_k) + \frac{1}{2} \sum_k \sum_l \phi_{kl} \log(p_k) \log(p_l).$$

In this paper we focus on the special case of $\theta_i = 0$, for simplicity, which is equivalent to imposing an income elasticity of one.

We also generate results for the mixed (or "random coefficients") logit demand system that is popular in empirical industrial economics research. This discrete choice demand system allows for heterogeneity in individual preferences. A consumer i receives utility u_{ij} for product j, where

$$u_{ij} = \xi_j + \beta_i x_j - \alpha_i p_j + \varepsilon_{ij}.$$

The ε_{ij} are drawn i.i.d. from a Type I Extreme Value distribution, and the preference coefficients are distributed normally such that

$$\begin{pmatrix} \beta \\ \alpha \end{pmatrix} \sim N\left(\begin{bmatrix} \mu_\beta \\ \mu_\alpha \end{bmatrix}, \begin{bmatrix} \sigma_\beta^2 & 0 \\ 0 & \sigma_\alpha^2 \end{bmatrix} \right).$$

The linear and log linear demand systems are given by the equations already discussed in Section 2.2.

3.3 Generating the logit, AIDS, linear, and log linear industries

Our goal is to form parameterizations for each of these demand systems. To that end, we use a calibration process, where we choose the value of the parameters so that the model can rationalize a randomly drawn set of market shares and margins. We use a particular draw of shares and margins to calibrate all four demand systems at the average cost draw, which is .5 for both products. We do this to ensure that the demand systems share the same properties at the average cost.

First, we draw a vector of shares shares (s_1 and s_2, such that $s_1 + s_2 < 1$ and the balance of the market consists of the outside good) and the margin for product 1. Shares are draw uniform on (0,1), and the margin is uniform on [.2,.8]. We impose the Bertrand-Nash first-order conditions of profit maximization. As the logit system is a three-parameter demand system, this vector is sufficient to identify the logit parameters.

Second, from the resulting equilibrium under logit demand, we obtain the margin of the second good and the matrix of first derivatives of demand. We combine these values with the shares and margin draws from the first step to calibrate the linear, log-linear, and AIDS equations. For the AIDS demand system, we give the outside good a price of one to calculate total expenditure, which we use to recover the constant in the revenue equation.

In our simulation, we use 150 Halton draws to fill out the space of shares and margins. We use eight cost specifications, as outlined in the next section. Particular values of parameters lead to poorly behaved equilibrium, i.e. those that do not coverge or result in firms making negative profits. We flag these equilbria and remove any industries (for all demand systems) that have a case where more than 10% of the draws are flagged. We then remove all remaining flagged observations across demand systems for a particular industry. This results in an average of 133 industries in each of the 8 cost specifications. With four demand systems per industry, we have a total of 133*8*4 data sets with an average of 198 observations each.

3.4 Generating the mixed logit industries

Unlike the other four demand systems, the mixed logit cannot be cleanly calibrated using the same inputs of shares, prices, and margins. This is because the structure of the model's demand equations do not allow for easy identification of the consumer heterogeneity parameters. The market share equations are nonlinear, allowing for multiple solutions even in the case of exact identification..

Therefore, in lieu of calibration, we simply select a range of values for each mixed logit parameter. We set $\xi_j = 10$ for both goods, and x_j to 1 for the first good and 0 for the second. For the preference coefficients, we use three values for each of μ_β, μ_α, σ^2_β, and σ^2_α, where the standard deviations are defined relative to the mean value. Industries are generated for each combination of these parameters, which are summarized below.

μ_β	μ_α	σ_β	σ_α
1	5	$\frac{1}{2}\mu_\beta$	$\frac{1}{10}\mu_\alpha$
2	20	μ_β	$\frac{1}{4}\mu_\alpha$
5	40	$2\mu_\beta$	$\frac{1}{2}\mu_\alpha$

3.5 Stochastic cost draws

To compare passthrough rates across demand systems, we construct equilibria based on stochastic cost draws that are common across industries and demand systems. For each cost draw, we solve for equilibrium prices and quantities. We assume that the marginal cost for each firm i is additive in costs that are observed and unobserved to the econometrician:

$$MC_i = OC_i + UC_i.$$

We construct different specifications of costs, which are based on two parameters: ω, the portion of costs that are observed,[6] and γ, the correlation in unobserved costs across firms. For each specification, we draw 200 unique cost combination.[7] We look at the following 8 specifications[8]:

Specification	1	2	3	4	5	6	7	8
ω	1	$\frac{2}{3}$	$\frac{1}{3}$	$\frac{2}{3}$	$\frac{1}{3}$	$\frac{1}{3}$	$\frac{2}{3}$	$\frac{1}{3}$
γ	0	0	0	$\frac{1}{4}$	$\frac{1}{4}$	$\frac{1}{2}$	1	1

We look at a range of specifications, from when costs are fully observed to when costs are only partially observed and the unobserved components are perfectly correlated. The standard deviation of marginal cost is fixed at .16, and the range is fixed from .1 to .9.

Our cost data-generating process uses four independent random variables (X_1, X_2, X_3, X_4) that follow symmetric Beta distributions in order to obtain the above restrictions. The cost components are given by

$$\begin{aligned}
OC_1 &= \delta X_1 \\
UC_1 &= (1-\delta)X_2 \\
OC_2 &= \delta X_3 \\
UC_2 &= a_0 + a_1 UC_1 + a_2 X_4.
\end{aligned}$$

Under the restrictions mentioned above, the parameters of the distributions and the equations above $(a_0, a_1 a_2, \delta)$ are identified. To illustrate the resulting The marginal distributions for MC_2 for specifications 1 and 9 are given below.

3.6 The reduced form regressions

Once we have generated a series of cost and price realizations for each industry, we then perform a series of reduced form regressions. These regressions are meant to mimic many of the specifications observed in the empirical literature on pass-through. [**should this be a separate section or is the explanation in section 4 enough?**]

3.7 Summary statistics

[**Should this go here or in results section 4?**] Table **??** provides summary statistics for the generated data. The mean own pass-through that arises with logit, linear, log-linear and mixed logit demand, respectively, equals 0.71, 0.53, 2.48 and 0.69. Own pass-through is constant only with linear and log-linear demand. The mean standard deviation in own

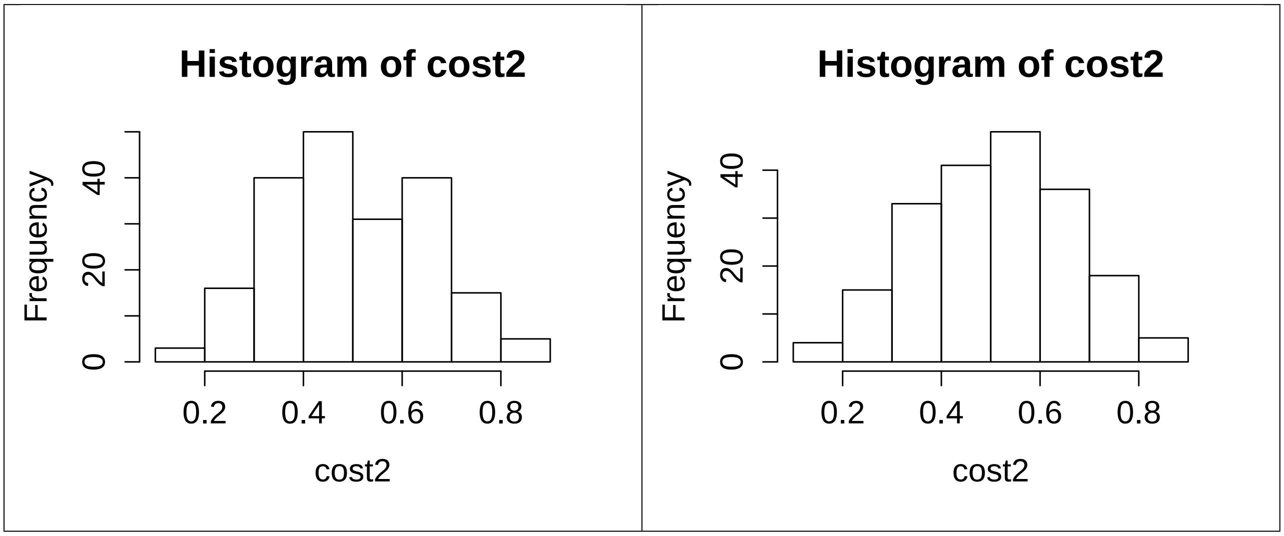
[6] This parameter gives both the proportion of the total range of costs and the proportion of the total variance of costs.

[7] We drop observations, i.e. cost draws, where the equilibrium price solver cannot find a solution or where the resulting equilibrium implies negative profits. If an observation meets one of these criteria, then we drop that observation across the four demand systems.

[8] For simplicity, we consider only cases where the correlation in unobserved costs is positive, which aligns with intuition.

Figure 3.1: Marginal Costs for Firm 2: Specifications 1 and 6

Specification 1	Specification 6



pass-through, within an industry, is 0.06 for logit demand and 0.13 for mixed logit demand. The mean cross pass-through that arises is 0.13, 0.12, 0.00, and 0.21, across the four demand systems. Again variability exists within industries for logit and mixed logit demand, where the mean standard deviation is 0.04 and 0.08, respectively. Cross pass-through is zero for log-linear demand – prices are neither (strict) strategic complements nor strategic substitutes in that system. Mean industry pass-through equals 0.84, 0.64, 2.48 and 0.90 across the demand systems. The equivalence between own and industry pass-through in the log-linear case is again due to the absence of strategic complementarity.

4 Results

4.1 Analysis

Our aim is to show how different features of a industry affect an econometrician's ability to estimate passthrough given price and costs. We use variation across industries in margins, shares, unobserved costs, and the nature of the demand. The variation reflects differences in industries we observe in the real world. Our simulations result in 133*8*4 unique industries to compare. We address how estimation accuracy changes according to the following concepts:

1. The flexibility of the regression equation.
2. Cost information available to the econometrician and correlation between unobserved costs.
3. Margins and shares as measures of the competitive nature of the industry.
4. The underlying demand system.

5. The estimation methodology, i.e. whether the full passthrough matrix is estimated or a single measure.

We use two industry-level measures to show the accuracy of the reduced-form regressions. The first, bias, shows the difference between average passthrough and average estimated passthrough for the entire industry. The second, mean absolute error, measures the average difference between actual passthrough and estimated passthrough for each firm within an industry. We regress these measures on average margins, average shares, proportion of costs that are unobserved, and correlation in unobserved costs (interacted with proportion unobserved) for each of the four demand systems.

Table 3 presents the results for bias when the full passthrough matrix is estimated. The table contains four sub-tables: one for each demand system. The top section of each sub-table provides select percentiles for the distribution of the error. In addition, we show the error for a "baseline" industry, which provides the measure when all costs are observed and the margins and shares are close to the average of all our industries. For example, there is no error in the linear demand system when all costs are observed. Below the distribution, we show the coefficients from our descriptive regressions.

The linear demand section of Table 3, located in the upper left, will serve as a useful example. First, let us examine the distribution of bias. The linear regression specification is accurate in recovering the average passthrough for the industry when demand is linear. In 90% of our industries, the bias was between -0.06 and 0. When we add a quadratic term for each cost, we see a shift toward no bias for the lower 50% of industries, which may be seen as a slight improvement. Adding a cubic term, however, causes the performance to fare far worse. Whereas observed bias is generally negative for the linear and quadratic specifications, it is generally positive with a cubic specification. Further, the magnitude of bias increases for a large portion of the industries. Over 25% of industries have an upward bias of over .318 with a cubic specification.

The regression coefficients describe how the error changes as we vary descriptive characteristics of the industry. For the linear demand case of Table 3, we see that unobserved costs have a negative and small relationship with bias for both the linear and quadratic regression specifications. With a cubic specification, the coefficient on ω is positive and meaningful. Moving from a world where all costs are observed to one where only half of the costs are observed would increase the bias from 0 to over .3. For our industries, with an average actual passthrough of .54, this is an increase of over 50%. Average industry shares follow a similar pattern, moving from a coefficient of -0.02 to 0.28 as the regression becomes more flexible.

In the next section we discuss the full set of results and provide some general conclusions.

4.2 Bias for Estimates of the Full Passthrough Matrix

Regression Specification Across all demand systems, the presence of quadratic terms for costs seems to shrink the bias for the lower half of the distribution. Further, it reduces the impact of shares, margins, and omitted costs. On the other hand, adding a cubic term makes the estimates much worse. For the upper quartiles of percent error, average passthrough is overstated by at least 48% to at least 61%, depending on the demand system.

Log-linear demand is the most sensitive in terms of absolute error, but the least in terms of percentage error.

Unobserved Costs It is no surprise that the presence of unobserved costs biases the predictions downward for the linear regression. In our data-generating process, unobserved costs are uncorrelated with observed costs, so the downward bias is analogous to attenuation bias that is found in cases of classical measurement error. Across all demand systems, the coefficient on ω implies a bias of less than 10% of the average passthrough value, which is small. Interestingly, this pattern no longer holds when we add cubic terms for the regression, Instead, the presence of unobserved costs results in positive and meaningful bias. The impact across demand systems is fairly consistent in terms of percent impact, though the slightly lower for log-linear demand, perhaps since the magnitudes are much greater.

In all cases, correlation in unobserved costs across firms has little impact on bias. Interestingly, the sign of the impact varies with the demand system, from consistently negative for logit demand to consistently positive for AIDS demand.

Margins and Quantities The signs and magnitudes of the impact of margins and quantities on bias vary across the demand systems. Without knowledge of the demand system, the econometrician cannot tell whether or not high margins and high quantities are correlated with positive or negative bias of passthrough estimates. In the linear and quadratric cases, the errors are small, so the sign may not be particularly meaningful. With a cubic regression, the informative power of each measure depends on the demand system. For linear demand and AIDS demand, both margins and quantities are positive related to bias. For logit, only quantities have a meaningful relationship, and for log-linear demand, neither seem to have much explanatory power.

4.3 Mean Absolute Error for Estimates of the Full Passthrough Matrix

Table 4 presents results for the mean absolute error by industry, i.e. the average absolute difference between actual passthrough and estimated passthrough by firm. We examine the same three categories of explanatory variables below.

Regression Specification Unlike the estimates for bias, the linear specification is the clear preference for attempting to predict individual firm passthrough, regardless of the demand system. The median MAE increases from approximately 5% of the true passthrough in a linear specification to 19% for a quadratic specification and 67% in a cubic specification. This indicates that the flexibility of the regression line does not allow it to better fit the true passthrough function in the industry, but rather to compensate for misspecification in an average sense, at least in the quadratic case. Thus, though a quadractic specification may improve the estimate of average passthrough for an industry, it peforms worse than a simple linear estimate when predicting individual firm passthrough.

Even in the best-performing linear specification, the results show that the demand system matters. With linear and log-linear demand, 95% of the individual estimates are within 10%

of the true passthrough. With logit, however, a quarter of the individual estimates are off by 12.6% or greater.

Unobserved Costs As expected, the presence of unobserved costs increase firm-level prediction error. This error is exaggerated the more flexible the regression. For example, in the linear case, the coeffiicent increases from 0.05 to 0.30 to 1.03 as a second- and third-order terms are added to the regression. These numbers are meaningful, as the average passthrough for the linear case is only 0.53.

Interestingly, correlation in unobserved costs matters only in the quadratic case. For linear, logit, and AIDS demand, the coefficient is positive and meaningful. For log-linear demand, however, the coefficient on the interaction of γ and ω is not economically meaningful for any of our specifications.

Margins and Quantities The relationship of these descriptive measures to the prediction error varies across the demand systems. For linear demand, the only strong relationship is that large quantities cause large errors in a cubic specification. For log-linear demand, increasing margins increases the absolute error, but when the errors are transformed into percentage errors the coefficient is small (less than 7% per quantity unit).

For logit demand, high margins are associated with decreased percentage errors, and high shares are associated with increased percentage errors. For AIDS, on the other hand, high quantities are associated with *decreased* percentage errors in the linear specification (and increased in the cubic specification). Thus, it is impossible to tell how high shares or high margins will affect the performance of passthrough estimates without tying the industry to a demand system.

4.4 Bias with a Single Regressor

One commonly used regression strategy is to simply regress price on own cost, and to ignore the effect of cross pass through on the coefficients. We perform this exercise, and present the bias and MAE for own passthrough in Tables 5 and 6 below.

Comparing Tables 3 and 5, we see that omitting the competitor's cost seems to shift up the distribution of bias. Though the observed costs were generated independently, we have selected only those industries that consistently converged to positive profits. This selection process resulted in a correlation (across all specifications) of 0.17. Omitting a positively correlated variable (which tends to drive prices up), would have the discovered effect of shifting up the bias. In the real world, we would expect some positive correlation between competitors' costs; therefore, this result is practical.

Regression Specification In addition, the 95-5 percentile range for the distribution of bias shrinks across all demand systems for the linear and quadratic regression specifications. For AIDS demand and a linear regression, for example, the 95-5 interval length is 0.137 when the full matrix is estimated and 0.093 when only the own cost is used. The range for the cubic regression specification, however, is increased when only own cost is used. This is further evidence that average passthrough can be better estimated with a quadratic specification, but that a cubic specification makes the estimates worse.

Unobserved Costs Using only a single regressor reduces the impact of unobserved cost on bias for the linear and quadratic regression specifications, and increases it for the cubic specification.

Margins and Quantities The coefficients on quantities and margins change when only the firm-specific cost is used. The changes depend on the demand system and the regression specification - there seems to be no general pattern.

4.5 Mean Absolute Error with a Single Regressor

Following the analysis in the previous section, we compare Tables 4 and 6. We observe the following:

1. Omitting the competitor's cost reduces the prediction error for the linear regression specification. The 95-5 range moves toward zero.

2. On the other hand, this strategy increases MAE for quadratic and cubic specifications.

3. Omitting the competitor's cost also reduces the impact of unobserved costs, but only for the linear regression specification.

4. The coefficients on shares and quantities change, but not in any consistent pattern.

5 Discussion

Based on our analysis, we recommend a strategy of using a quadratic regression using only the single firm's cost when attempting to recover average industry passthrough and there is concern that costs are not perfectly observed.

When attempting to predict firm-specific passthrough, however, we recommend using a linear regression specification using only the single firm's cost.

Estimates of cross passthrough are in general less reliable.

6 Conclusion

[To be completed.]

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Table 1: Average Own Passthrough by Industry

		Demand System			
		Linear	Log-linear	Logit	AIDS
Distribution	5%	0.502	1.316	0.363	0.746
	25%	0.512	1.565	0.619	0.868
	50%	0.528	1.99	0.712	1.115
	75%	0.554	2.811	0.825	1.44
	95%	0.628	4.265	0.954	2.555
Coefficient	ω	0	0.018	0.001	-0.003
	$\omega \times \gamma$	0	0.096	-0.004	0.016
	Avg. Margins	0.004	5.441	0.149	2.797
	Avg. Shares	0.365	0.23	-0.715	-0.392

Table 2: Average Cross Passthrough by Industry

		Demand System			
		Linear	Log-linear	Logit	AIDS
Distribution	5%	0.021	0	0.009	0.057
	25%	0.088	0	0.044	0.226
	50%	0.131	0	0.087	0.297
	75%	0.188	0	0.149	0.436
	95%	0.287	0	0.283	0.773
Coefficient	ω	0	0	0	0.002
	$\omega \times \gamma$	0	0	0.009	-0.002
	Avg. Margins	0.032	0	-0.052	0.706
	Avg. Shares	0.711	0	0.79	1.861

Table 3: Bias for Full Passthrough Matrix

Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	-0.056	-0.046	-0.004
	25%	-0.028	-0.021	0.001
	50%	-0.02	-0.015	0.072
	75%	-0.009	-0.011	0.318
	95%	0	0	0.412
Coefficient	ω	-0.049	-0.033	0.623
	$\omega \times \gamma$	-0.009	-0.005	0.002
	Avg. Margins	0.021	0.019	0.063
	Avg. Shares	-0.023	-0.022	0.277

Log-Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	-0.186	-0.136	-0.012
	25%	-0.1	-0.081	0.009
	50%	-0.066	-0.057	0.069
	75%	-0.032	-0.04	0.96
	95%	0	0	1.816
Coefficient	ω	-0.189	-0.124	2.099
	$\omega \times \gamma$	0.01	0.01	0.047
	Avg. Margins	-0.136	-0.116	1.396
	Avg. Shares	-0.028	-0.028	0.011

Logit		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	-0.002	0	-0.001
	5%	-0.057	-0.05	-0.002
	25%	-0.038	-0.029	0.002
	50%	-0.023	-0.021	0.037
	75%	-0.014	-0.014	0.41
	95%	-0.001	0	0.467
Coefficient	ω	-0.063	-0.047	0.757
	$\omega \times \gamma$	0.001	0.004	0.016
	Avg. Margins	0.034	0.03	0.082
	Avg. Shares	0.014	0.013	0.067

AIDS		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.003	-0.002	0.001
	5%	-0.134	-0.103	-0.006
	25%	-0.06	-0.05	0.007
	50%	-0.035	-0.031	0.14
	75%	-0.015	-0.019	0.688
	95%	0.003	-0.001	1.25
Coefficient	ω	-0.107	-0.055	1.508
	$\omega \times \gamma$	-0.034	-0.025	-0.02
	Avg. Margins	-0.07	-0.059	0.937
	Avg. Shares	-0.033	-0.034	0.351

Table 4: MAE for Full Passthrough Matrix

Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	0
	25%	0.009	0.027	0.05
	50%	0.02	0.104	0.363
	75%	0.028	0.184	0.544
	95%	0.056	0.28	0.708
Coefficient	ω	0.049	0.303	1.029
	$\omega \times \gamma$	0.01	0.108	0.014
	Avg. Margins	-0.023	-0.032	0.049
	Avg. Shares	0.024	0.108	0.493

Log-Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	0
	25%	0.032	0.074	0.15
	50%	0.066	0.381	0.738
	75%	0.1	0.673	1.654
	95%	0.186	1.215	3.121
Coefficient	ω	0.189	1.386	3.508
	$\omega \times \gamma$	-0.007	0.023	0.063
	Avg. Margins	0.133	0.918	2.513
	Avg. Shares	0.028	0.055	0.09

Logit		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.05	0.026	0.027
	5%	0.017	0.015	0.014
	25%	0.036	0.043	0.076
	50%	0.048	0.121	0.303
	75%	0.078	0.256	0.707
	95%	0.138	0.321	0.801
Coefficient	ω	0.025	0.375	1.24
	$\omega \times \gamma$	-0.017	0.076	0.009
	Avg. Margins	-0.194	-0.093	-0.01
	Avg. Shares	0.044	-0.008	0.108

AIDS		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.08	0.028	0.025
	5%	0.031	0.023	0.019
	25%	0.064	0.084	0.119
	50%	0.09	0.201	0.53
	75%	0.125	0.433	1.169
	95%	0.195	0.819	2.136
Coefficient	ω	0.022	0.716	2.407
	$\omega \times \gamma$	-0.002	0.243	0.014
	Avg. Margins	0.129	0.554	1.63
	Avg. Shares	-0.214	-0.078	0.664

Table 5: Bias for Own Passthrough (Own Cost Only)

Linear		Linear	Quadratic	Cubic
Distribution	baseline	-0.004	-0.004	-0.002
	5%	-0.021	-0.016	-0.003
	25%	-0.008	-0.008	0.005
	50%	-0.005	-0.003	0.142
	75%	0.002	0.006	0.362
	95%	0.016	0.022	0.479
Coefficient	ω	0.003	0.016	0.705
	$\omega \times \gamma$	-0.009	-0.005	0.014
	Avg. Margins	0.013	0.012	0.052
	Avg. Shares	0.041	0.043	0.351

(Columns: Regression Specification)

Log-Linear		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	-0.12	-0.078	-0.01
	25%	-0.067	-0.051	0.017
	50%	-0.047	-0.035	0.145
	75%	-0.028	-0.026	1.038
	95%	0	0	1.963
Coefficient	ω	-0.116	-0.061	2.268
	$\omega \times \gamma$	0.009	0.008	0.046
	Avg. Margins	-0.09	-0.066	1.508
	Avg. Shares	-0.022	-0.022	0.017

Logit		Linear	Quadratic	Cubic
Distribution	baseline	-0.005	-0.004	-0.004
	5%	-0.031	-0.028	-0.004
	25%	-0.017	-0.013	0.006
	50%	-0.011	-0.008	0.09
	75%	-0.003	-0.001	0.459
	95%	0.018	0.022	0.512
Coefficient	ω	-0.014	-0.002	0.842
	$\omega \times \gamma$	0.003	0.006	0.027
	Avg. Margins	0.019	0.016	0.066
	Avg. Shares	0.076	0.073	0.123

AIDS		Linear	Quadratic	Cubic
Distribution	baseline	-0.008	-0.009	-0.003
	5%	-0.048	-0.032	-0.004
	25%	-0.017	-0.014	0.017
	50%	-0.006	-0.006	0.242
	75%	0.009	0.02	0.779
	95%	0.045	0.06	1.437
Coefficient	ω	0.02	0.06	1.704
	$\omega \times \gamma$	-0.033	-0.025	0.009
	Avg. Margins	-0.005	0.011	1.039
	Avg. Shares	0.115	0.115	0.505

Table 6: MAE for Own Passthrough (Own Cost Only)

Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.004	0.006	0.01
	5%	0.001	0.004	0.008
	25%	0.004	0.014	0.038
	50%	0.007	0.106	0.392
	75%	0.013	0.192	0.578
	95%	0.025	0.287	0.755
Coefficient	ω	0.018	0.321	1.093
	$\omega \times \gamma$	-0.004	0.109	0.031
	Avg. Margins	-0.016	-0.032	0.043
	Avg. Shares	0.017	0.104	0.52

Log-Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	0
	25%	0.029	0.062	0.14
	50%	0.047	0.373	0.801
	75%	0.067	0.684	1.736
	95%	0.12	1.235	3.271
Coefficient	ω	0.116	1.42	3.694
	$\omega \times \gamma$	-0.005	0.023	0.066
	Avg. Margins	0.087	0.919	2.609
	Avg. Shares	0.023	0.052	0.09

Logit		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.05	0.026	0.026
	5%	0.015	0.013	0.015
	25%	0.026	0.035	0.063
	50%	0.041	0.119	0.318
	75%	0.076	0.263	0.747
	95%	0.136	0.327	0.842
Coefficient	ω	0.008	0.392	1.316
	$\omega \times \gamma$	-0.022	0.079	0.024
	Avg. Margins	-0.207	-0.097	-0.014
	Avg. Shares	0.048	-0.003	0.12

AIDS		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.079	0.032	0.034
	5%	0.023	0.025	0.031
	25%	0.059	0.063	0.09
	50%	0.084	0.193	0.575
	75%	0.117	0.445	1.24
	95%	0.185	0.834	2.266
Coefficient	ω	0.008	0.77	2.574
	$\omega \times \gamma$	-0.031	0.24	0.052
	Avg. Margins	0.122	0.553	1.679
	Avg. Shares	-0.255	-0.09	0.697

Table 7: Bias for Cross Passthrough

Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	-0.052
	25%	0.035	0.033	-0.029
	50%	0.065	0.062	-0.009
	75%	0.078	0.077	0
	95%	0.103	0.102	0.077
Coefficient	ω	0.123	0.124	0.064
	$\omega \times \gamma$	0.001	0	-0.134
	Avg. Margins	-0.008	-0.009	-0.02
	Avg. Shares	0.074	0.073	0.057

Log-Linear		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	-0.233
	25%	0.098	0.091	-0.123
	50%	0.19	0.188	-0.084
	75%	0.267	0.265	-0.04
	95%	0.482	0.479	0
Coefficient	ω	0.482	0.487	-0.176
	$\omega \times \gamma$	-0.009	-0.008	-0.035
	Avg. Margins	0.467	0.455	-0.252
	Avg. Shares	0.039	0.039	0.013

Logit		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.004	0.002	0.006
	5%	0.001	0.001	-0.059
	25%	0.049	0.045	-0.038
	50%	0.064	0.062	-0.009
	75%	0.099	0.099	0.005
	95%	0.123	0.123	0.073
Coefficient	ω	0.144	0.149	0.028
	$\omega \times \gamma$	0	0	-0.112
	Avg. Margins	-0.008	-0.009	-0.062
	Avg. Shares	-0.003	-0.001	0.125

AIDS		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	-0.013	-0.005	-0.005
	5%	-0.012	-0.005	-0.133
	25%	0.067	0.061	-0.064
	50%	0.126	0.122	-0.03
	75%	0.175	0.175	-0.001
	95%	0.302	0.3	0.197
Coefficient	ω	0.307	0.305	0.185
	$\omega \times \gamma$	0.009	0.007	-0.323
	Avg. Margins	0.268	0.262	-0.081
	Avg. Shares	0.066	0.064	0.206

Table 8: MAE for Cross Passthrough

Linear		Regression Specification: Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	0
	25%	0.035	0.038	0.098
	50%	0.065	0.065	0.148
	75%	0.078	0.078	0.171
	95%	0.103	0.103	0.214
Coefficient	ω	0.123	0.119	0.061
	$\omega \times \gamma$	0.002	0.009	0.125
	Avg. Margins	-0.009	-0.015	-0.002
	Avg. Shares	0.074	0.076	0.154

Log-Linear		Regression Specification: Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	0	0	0
	25%	0.098	0.113	0.384
	50%	0.19	0.199	0.491
	75%	0.267	0.274	0.708
	95%	0.482	0.479	1.116
Coefficient	ω	0.482	0.461	0.612
	$\omega \times \gamma$	-0.007	0.006	0.039
	Avg. Margins	0.466	0.474	1.354
	Avg. Shares	0.039	0.042	0.09

Logit		Regression Specification: Linear	Quadratic	Cubic
Distribution	baseline	0.025	0.025	0.029
	5%	0.016	0.013	0.015
	25%	0.052	0.056	0.127
	50%	0.084	0.083	0.185
	75%	0.106	0.109	0.219
	95%	0.129	0.133	0.256
Coefficient	ω	0.117	0.127	0.109
	$\omega \times \gamma$	0.005	0.005	0.092
	Avg. Margins	-0.066	-0.069	0.019
	Avg. Shares	0.058	0.061	-0.038

AIDS		Regression Specification: Linear	Quadratic	Cubic
Distribution	baseline	0.065	0.029	0.028
	5%	0.048	0.025	0.021
	25%	0.084	0.081	0.208
	50%	0.134	0.133	0.302
	75%	0.179	0.181	0.425
	95%	0.302	0.305	0.73
Coefficient	ω	0.234	0.256	0.132
	$\omega \times \gamma$	0.005	0.013	0.258
	Avg. Margins	0.278	0.278	0.705
	Avg. Shares	0.103	0.082	0.124

Table 9: Alternative Formatting for Tables

		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	-0.056	-0.046	-0.004
	25%	-0.028	-0.021	0.001
	50%	-0.02	-0.015	0.072
	75%	-0.009	-0.011	0.318
	95%	0	0	0.412
Coefficient	ω	-0.049	-0.033	0.623
	$\omega \times \gamma$	-0.009	-0.005	0.002
	Avg. Margins	0.021	0.019	0.063
	Avg. Shares	-0.023	-0.022	0.277

(a) Linear Demand

		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0	0	0
	5%	-0.186	-0.136	-0.012
	25%	-0.1	-0.081	0.009
	50%	-0.066	-0.057	0.069
	75%	-0.032	-0.04	0.96
	95%	0	0	1.816
Coefficient	ω	-0.189	-0.124	2.099
	$\omega \times \gamma$	0.01	0.01	0.047
	Avg. Margins	-0.136	-0.116	1.396
	Avg. Shares	-0.028	-0.028	0.011

(b) Log-linear Demand

		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	-0.002	0	-0.001
	5%	-0.057	-0.05	-0.002
	25%	-0.038	-0.029	0.002
	50%	-0.023	-0.021	0.037
	75%	-0.014	-0.014	0.41
	95%	-0.001	0	0.467
Coefficient	ω	-0.063	-0.047	0.757
	$\omega \times \gamma$	0.001	0.004	0.016
	Avg. Margins	0.034	0.03	0.082
	Avg. Shares	0.014	0.013	0.067

(c) Logit Demand

		Regression Specification		
		Linear	Quadratic	Cubic
Distribution	baseline	0.003	-0.002	0.001
	5%	-0.134	-0.103	-0.006
	25%	-0.06	-0.05	0.007
	50%	-0.035	-0.031	0.14
	75%	-0.015	-0.019	0.688
	95%	0.003	-0.001	1.25
Coefficient	ω	-0.107	-0.055	1.508
	$\omega \times \gamma$	-0.034	-0.025	-0.02
	Avg. Margins	-0.07	-0.059	0.937
	Avg. Shares	-0.033	-0.034	0.351

(d) AIDS Demand