UNIVERSIDAD DEL CEMA
Buenos Aires
Argentina

Serie
DOCUMENTOS DE TRABAJO

Área: Economía

COMPETITION AND PRODUCT DIFFERENTIATION IN THE ARGENTINE CHOCOLATE BAR INDUSTRY

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Mayo 2024
Nro. 869

www.cema.edu.ar/publicaciones/doc_trabajo.html
UCEMA: Av. Córdoba 374, C1054AAP Buenos Aires, Argentina
ISSN 1668-4575 (impreso), ISSN 1668-4583 (en línea)
Editor: Jorge M. Streb; Coordinador del Departamento de Investigaciones Maximiliano Ivickas

For Valeria Dowding, *in memoriam*.

Competition and Product Differentiation in the Argentine Chocolate Bar Industry

Germán Coloma *

Abstract

This paper analyzes the behavior of the Argentine chocolate bar industry during the period 2019-2022. It mainly focuses on the level of competition between the firms in the industry, estimating conduct parameters that signal the existence of harder or softer competition. The estimations change considerably under different demand specifications, and also if we explicitly model product differentiation at the level of the supplying firms. This allows discarding extreme hypotheses such as perfect competition and collusion, and it slightly favors the existence of quantity (Cournot) competition over price (Bertrand) competition.

Keywords: Chocolate bars, Argentina, competition, product differentiation, conduct parameters.

JEL Classification: C32, L13, L66.

1. Introduction

Competition under product differentiation has several features that do not appear in industries with homogenous products. The main distinctive characteristic is probably the fact that there is a sharp distinction between perfect (or price-taking) competition and price (or Bertrand) competition.

Under product homogeneity, if firms act as price-takers, then they cannot set prices, and their only possible choice has to do with the quantities that they are willing to sell in the market. Conversely, under product differentiation, firms can act as price-takers of the other firms' prices and at the same time set their own prices, and that is a completely different kind of competition than the one that occurs when all prices are exogenous to the firms. It is also different from other types of competition in which firms do not take other firms' prices as

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given (for example, cases in which they react to the other firms' quantity decisions) and, of course, different from cases in which they cooperate or collude with other firms in order to set prices or quantities.[1]

In this paper we will see the empirical difference between all those alternatives, using data from the Argentine chocolate bar industry. At first, we will model competition through a homogeneous-product approach, under which there is a single demand function and a single supply price function. That will allow us to calculate "conduct parameters" that try to estimate if the industry is close to perfect competition or to monopoly, with intermediate values for cases of imperfect competition.

Using data for quantities and prices of the two main firms that operate in the industry, however, we will be able to model competition between those two firms, and that competition will have an implicit assumption of product differentiation. We will therefore be able to distinguish between perfect competition, price competition and quantity competition, and to measure the individual market power of each firm, as opposed to the possible existence of "joint market power" (if those firms coordinate their decisions between themselves).

The structure of this paper will be the following. In section 2 we will briefly describe the Argentine chocolate bar industry during the period 2019-2022, while in section 3 we will estimate conduct parameters under different single-demand assumptions. Section 4, in turn, will introduce product differentiation and the effect that it has on competition. We will also estimate individual and joint conduct parameters for the two main chocolate bar manufacturers. Section 5, finally, will be devoted to the conclusions of the whole paper.

2. The Argentine chocolate bar industry

The chocolate bar industry in Argentina is basically constituted by firms that manufacture and distribute chocolate bars in different outlets such as supermarkets, grocery stores and candy stores (*kioscos*). This industry is highly concentrated in two main suppliers: Arcor (which has a revenue market share around 55%) and Mondelez (whose market share is roughly 30%). The remaining 15% of the market is supplied by several other manufacturers, of which the main ones are Nestlé and Georgalos (whose market shares are

[1] For a thorough treatment of the differences between all those concepts, see Vives (1999), chapters 3-6.

around 3% each).

Chocolate bars can be considered as a single product, but they are subject to a considerable differentiation due to characteristics such as size, type of chocolate (e.g., dark chocolate, white chocolate, milk chocolate) and combination with other products (e.g., chocolate with almonds, with peanuts, etc.). They are also substitutable by other goods such as chocolate cookies, peanut paste bars and nougats, but in this paper the analysis will not be extended to those goods.

In Argentina, chocolate bars are sold under several brands, which are controlled by the different supplying firms. The most important ones are Cofler, Block, Aguila, Hamlet and Tofi (Arcor), Milka, Toblerone and Shot (Mondelez), Kit Kat and Suflair (Nestlé), Full Maní (Georgalos), Felfort, etc. The main data concerning the Argentine chocolate bar industry are summarized on Table 1, where we can see the evolution of quantities, prices, and revenue market shares during the period 2019-2022.[2]

1. Data from the Argentine chocolate bar industry

Concept / Year	**2019**	**2020**	**2021**	**2022**	**Average**
Quantities (kg)					
Mondelez	4,370,844	3,373,587	4,529,151	5,234,084	4,376,917
Arcor	9,347,139	7,499,005	10,475,180	11,445,355	9,691,670
Others	1,760,605	1,614,723	3,607,141	4,955,782	2,984,563
Total	15,478,588	12,487,315	18,611,472	21,635,221	17,053,149
Prices (US$/kg)					
Mondelez	20.97	20.40	25.35	28.86	23.89
Arcor	17.92	17.01	18.36	23.65	19.23
Others	20.44	17.41	16.76	20.52	18.78
Total	19.07	17.98	19.75	24.19	20.35
Revenue market shares (%)					
Mondelez	31.05%	30.66%	31.24%	28.86%	29.91%
Arcor	56.75%	56.82%	52.32%	51.71%	54.92%
Others	12.19%	12.52%	16.45%	19.43%	15.17%
HHI	0.4158	0.4205	0.3862	0.3545	0.3942

Source: Own calculations based on data from A. C. Nielsen.

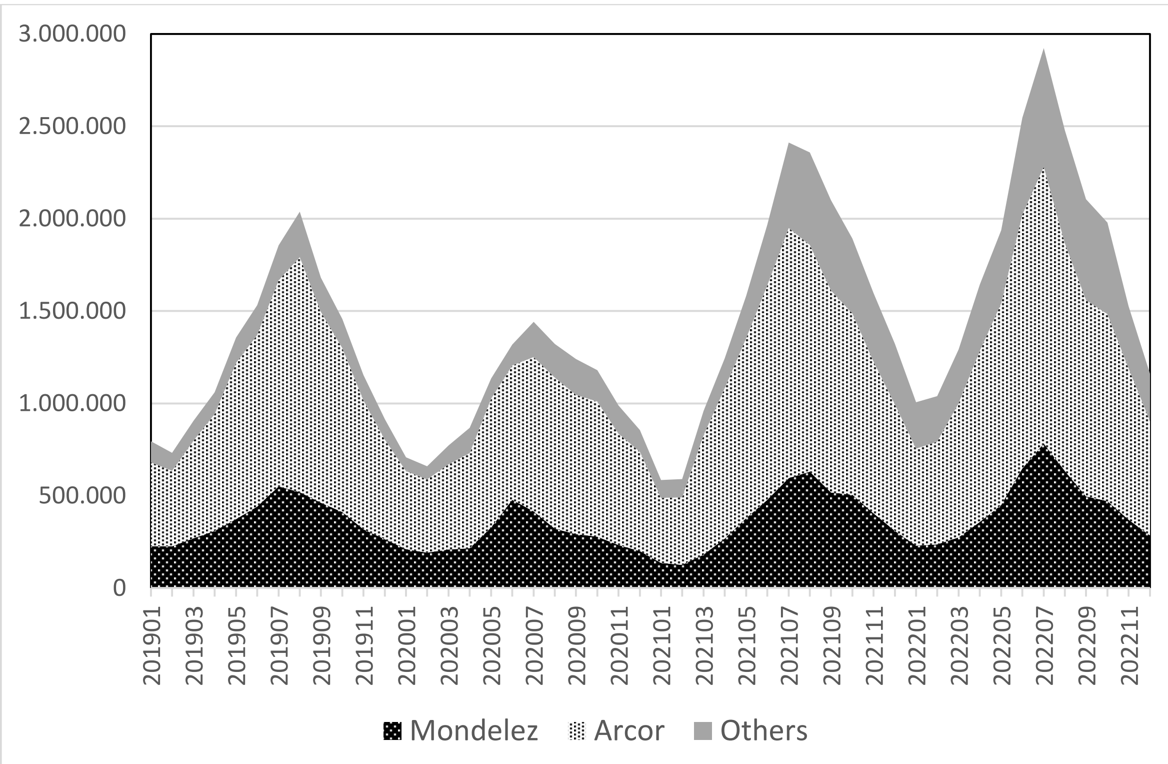
The last line of Table 1 shows the values of the Herfindahl and Hirschman index (HHI) for the industry as a whole. This index is the sum of the squares of the firms' revenue

[2] All the information concerning the Argentine chocolate bar industry that we use in this study comes from data sets elaborated by the consulting firm A. C. Nielsen. Prices are expressed in US dollars, converted into such currency by using exchange rate information published by the Central Bank of Argentina (BCRA).

market shares, and it measures the concentration of the industry. It can also be seen as a weighted average of those revenue shares, measured in a scale from 0 to 1.

Chocolate bars are subject to some seasonality of consumption. They are typically consumed in larger quantities during the Winter season (which in Argentina lasts from June to September). This can be seen in Figure 1, in which we see that this seasonality basically applies to all chocolate brands, no matter whether they are supplied by Mondelez, Arcor or other firms.

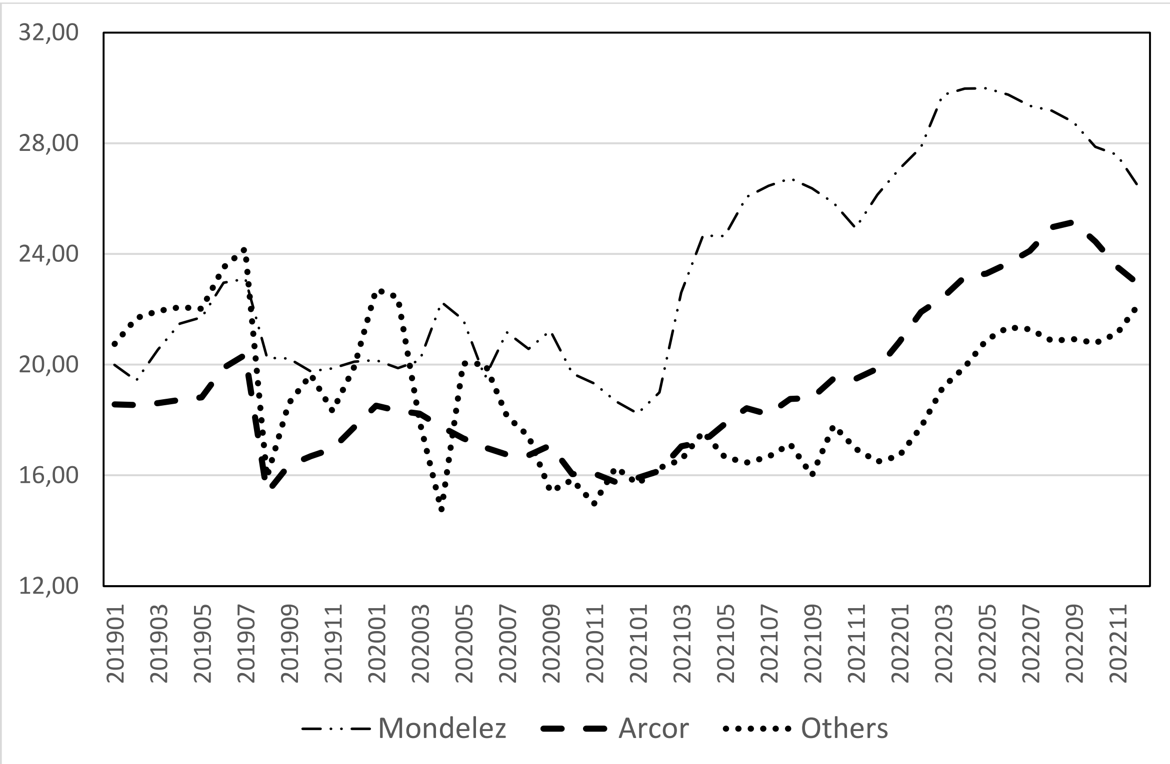
1. Chocolate bar sales in Argentina (kg)



Source: Own calculations based on data from A. C. Nielsen.

The evolution of prices, depicted on Figure 2, shows instead a considerable variation among firms. We can observe that, in general, the Mondelez chocolate bars are on average more expensive than Arcor's and other firms' bars, and that the evolution of those figures is considerably different. As prices are here expressed in US dollars per kilogram, part of their variation is caused by changes in the exchange rate between the US dollar and the Argentine peso, which in the period under analysis were considerably large.[3] Note that the prices reported here are in all cases consumer prices, i.e., they are the average prices paid by final consumers when they buy chocolate bars.

2. Chocolate bar prices in Argentina (US$/kg)



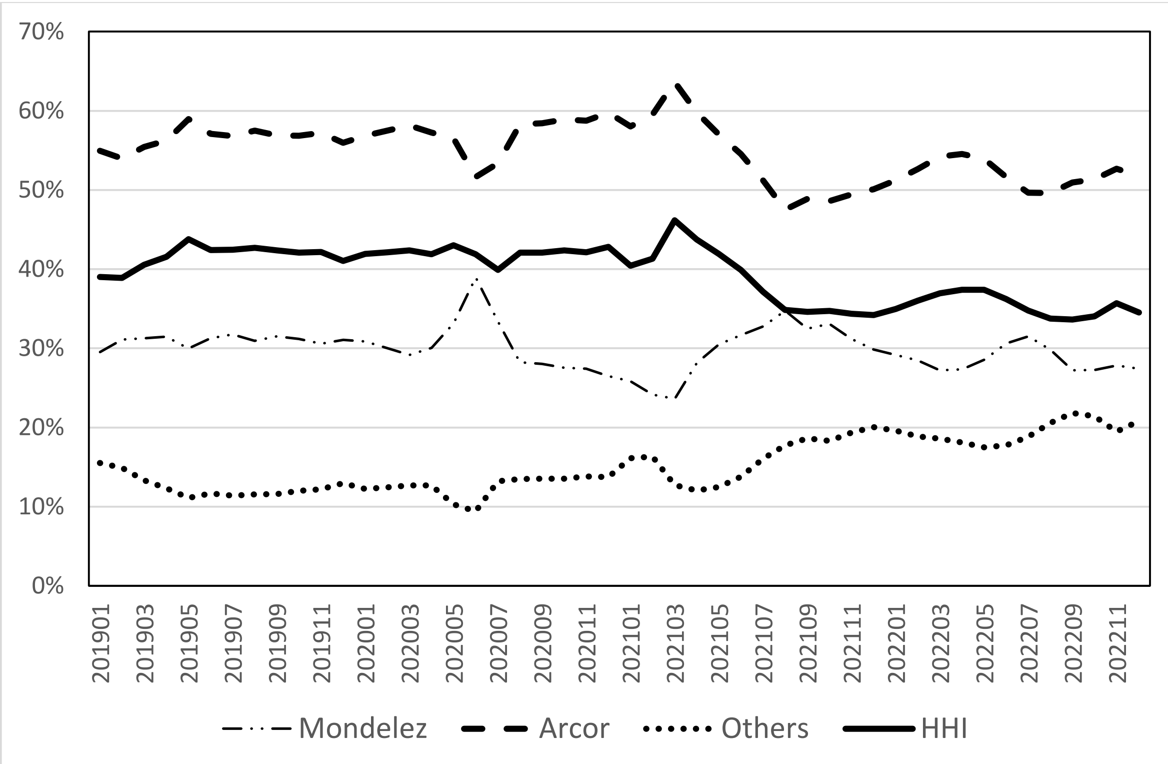
Source: Own calculations based on data from A. C. Nielsen.

The evolution of revenue market shares during the period 2019-2022 is much more stable than the evolution of prices. In Figure 3 we can see that, during the period under analysis, Arcor has always been the firm with the largest revenue share, and Mondelez has always been second in the market share ranking. We can nevertheless observe a minor change that becomes evident in 2021 and 2022, which is related to an increase in the share of the other firms that participate in the Argentine chocolate bar industry. This generates a reduction in the HHI concentration index, which in the last two years is always below 0.4, while in the

[3] The use of the US dollars to express prices in this section is due to the large inflation rates that Argentina experienced during the period under analysis, which makes intertemporal price comparisons useless. In the following sections, the computation problem caused by inflation rates will be solved in a different way, using the evolution of several price indices such as the Argentine consumer price index, and the wholesale price indices for chocolate products and milk products.

previous years it had typically been above that threshold.

3. Revenue market shares and concentration (%)



Source: Own calculations based on data from A. C. Nielsen.

The determinants of the evolution of prices, quantities and market shares described in this section of the paper may be due to some factors related to the kind of competition that takes place between the different suppliers of the Argentine chocolate bar industry. This competition will be analyzed in the following sections using different strategies, including supply and demand estimations, conduct parameters, and hypothesis testing of models that aim to represent the behavior of the firms that operate in the industry.

3. Competition and conduct parameters

One way to model competition in a market is to consider the corresponding demand and supply relationships that occur in that market. This essentially implies running regressions to estimate a demand function (which relates quantity values with price values and with other variables that shift demand along time) and a supply price function (which relates price values with cost variables and with some measurement of the exercise of the market power that is supposed to exist in the industry under analysis).[4]

In order to perform demand and supply estimations, it is necessary to have price and quantity data (such as the ones that we described in section 2) together with some data on demand and cost shifters. These last data will be here obtained using public information for the Argentine economy, which is elaborated by the National Institute of Statistics and the Census of Argentina (INDEC). In particular, we will use series for the consumer price index (IPC), the monthly estimator of economic activity (EMAE), the wholesale price index of chocolate products (IPCHOC), and the wholesale price index of milk products (IPLACT).[5]

The consumer price index and the estimator of economic activity will in turn be used to build a "nominal income index", that aims to reflect the evolution of chocolate consumers' nominal income along time. This index (YNOM) is simply the multiplication of IPC and EMAE, and it will be included as the main determinant of chocolate bar demand, together with the price of chocolate bars.

Our first model of demand and supply of chocolate bars in Argentina is a linear model that follows this specification:

$$QTOTAL = c(1) + c(2)*TREND + c(3)*WINTER + c(4)*PTOTAL + c(5)*YNOM \qquad (1)\ ;$$

$$PTOTAL = c(7) + c(8)*IPCHOC + c(9)*IPLACT - c(10)/c(4)*QTOTAL \qquad (2)\ ;$$

where QTOTAL is total chocolate bar sales measured in kilograms, PTOTAL is the average price of chocolate bars measured in Argentine pesos per kilogram, WINTER is a dummy variable that takes a value equal to one for the months of June, July, August and September (and zero otherwise), and TREND is a variable that goes from 1 to 48 as time goes by in the data sample (which begins in January 2019 and ends in December 2022).

As we can see, Equation 1 represents the demand function for chocolate bars, while Equation 2 represents the supply price function. Coefficients c(1) to c(10) are parameters to be estimated using a regression procedure, and they can be interpreted as the effects that different variables have on demand or supply. Coefficient c(3), for example, measures the increase in chocolate bar demand that occurs during the Winter season, while c(5) is the

[4] For a more complete explanation of the empirical logic behind these models, see Perloff, Karp and Golan (2007), chapter 3.

[5] These last two indices are in fact chapters of the domestic wholesale price index (IPIM), published monthly by INDEC.

marginal effect that a change in consumers' nominal income has on the quantity demanded. In turn, coefficients c(8) and c(9) represent the effects that changes in input prices (in this case, wholesale chocolate and milk prices) have on the marginal cost of chocolate bars.

Coefficient c(4) has a particular interpretation, since it is an estimate of the slope of the demand function. It should therefore have a negative value, that can be related to the behavior of the supply price equation. Indeed, if firms have some kind of market power in this industry, it is expected that their supply price be inversely related to the value of c(4), since demands which are steeper generate incentives for firms to exploit that characteristic in order to obtain higher profits. This interaction, however, crucially depends on the level of competition that the industry exhibits, that is measured here by coefficient c(10), which is an estimate of the so-called "conduct parameter" of the industry.

The idea behind this relationship has to do with the interpretation of Equation 2 as the sum of a certain marginal cost (equal to "c(7) +c(8)*IPCHOC +c(9)*IPLACT") and a margin between price and marginal cost (equal to "-c(10)/c(4)*QTOTAL"). This margin could be equal to zero if "c(10) = 0", and equal to "-1/c(4)*QTOTAL" if "c(10) = 1". This last situation is equivalent to the case of a monopoly industry, while the first one could be identified with a situation of perfect competition.[6]

2. Linear demand and supply regression results

Variable / Results	Coefficient	Std. Error	t-statistic	Probability
Demand equation				
Constant	1064613	155255.9	6.857146	0.0000
Trend	9666.681	9025.509	1.071040	0.2871
Winter	805810.5	90562.21	8.897867	0.0000
Price	-1968.481	645.2246	-3.050846	0.0030
Nominal income	49.51725	13.62422	3.634500	0.0005
Supply price equation				
Constant	-202.7624	18.62655	-10.88567	0.0000
Chocolate price index	0.245525	0.181288	1.354337	0.1791
Milk price index	2.871870	0.218144	13.16504	0.0000
Conduct parameter	0.041255	0.032599	1.265555	0.2091

Table 2 shows the main results of the estimation of equations 1 and 2, performed using the methodology of three-stage least squares.[7] This methodology allows to consider

[6] For a good explanation of the theory of conduct parameters, see Davis and Garcés (2012), chapter 6.
[7] This estimation, like all the others whose results are reported in this paper, was performed using the software

the fact that some independent variables are endogenous to the system (which is the case of PTOTAL and QTOTAL), and the fact that the estimation errors of the two equations could be correlated. To solve both statistical problems, the three-stage least-square method replaces the endogenous variables by linear functions of all the other (exogenous) variables, and it also incorporates the correlation between estimation errors in the calculation of the final coefficients.[8]

The results obtained can in general be considered good, and they are coherent with the assumptions of the model. Both equations generate a good fit of the data, since their corresponding R^2 coefficients of determination are equal to 0.736759 (demand) and 0.998016 (supply). Moreover, all coefficient signs are the expected ones, since WINTER, YNOM, IPCHOC and IPLACT have positive coefficients, and PTOTAL has a negative coefficient in the demand equation. The conduct parameter c(10) also has a positive sign, but its absolute value (0.041255) is relatively close to zero (and it is not significantly different from that number, either). Its probability value is 0.2091, which implies that it is not significant at a 10% probability level.

The relative value of c(10) in this estimation can be seen as an indication that the industry under analysis is close to perfect competition and far away from monopoly. This is reinforced by the fact that, if we run a Wald test of the restriction "c(10) = 1", the implied probability value is virtually zero, and this can be read as a sign that the monopoly hypothesis is impossible under this model specification.

The conclusion of the previous paragraph, however, is strongly dependent of the linear specification used to model demand under Equation 1. If we alternatively use a logarithmic demand specification, our model could be rewritten in the following way:

$$LOG(QTOTAL) = c(1) + c(2)*TREND + c(3)*WINTER + c(4)*LOG(PTOTAL/YNOM) \quad (3);$$
$$PTOTAL = c(7) + c(8)*IPCHOC + c(9)*IPLACT - c(10)/c(4)*PTHAT \quad (4);$$

where LOG indicates the natural logarithm of the corresponding variable, and PTHAT is an artificial variable that replaces PTOTAL by the fitted values of a least-square regression of that variable against a constant, TREND, WINTER and YNOM.

This new demand specification assumes that the relationship between QTOTAL and

package EViews 10. The complete results of all estimations are shown in Appendix 2.
[8] For a thorough explanation of the three-stage least-square method, see Greene (2012), chapter 10.

PTOTAL is exponential rather than linear, and it also assumes that the demand function is homogenous of degree zero in prices and income.[9] This last feature implies that, if nominal income and prices changed in the same proportion, then consumers would not change their consumption decisions.

Under this specification, coefficient c(4) can be interpreted as a price elasticity, rather than a slope of the demand function. It also serves to calculate the margin between price and marginal cost. This margin can now be defined as equal to “-c(10)/c(4)*PTHAT”, where “c(10)” is the new conduct parameter of the system (which once again must be equal to zero under perfect competition and equal to one under monopoly).

The main results of this new regression are reported on Table 3. They were obtained under the same methodology used for the previous regression (three-stage least squares), assuming that all the independent variables are exogenous except PTOTAL and PTHAT.

3. Logarithmic demand and supply regression results

Variable / Results	Coefficient	Std. Error	t-statistic	Probability
Demand equation				
Constant	5.118936	1.910314	2.679631	0.0088
Trend	0.003635	0.003079	1.180609	0.2409
Winter	0.565893	0.068238	8.292909	0.0000
Price/Nominal income	-2.408260	0.542196	-4.441674	0.0000
Supply price equation				
Constant	-161.2958	18.02152	-8.950175	0.0000
Chocolate price index	0.107897	0.143147	0.753749	0.4530
Milk price index	2.492638	0.244852	10.18016	0.0000
Conduct parameter	0.427758	0.191383	2.235082	0.0279

Most results obtained here are qualitatively similar to the ones gotten under the previous linear demand specification. The corresponding R^2 coefficients are now equal to 0.701003 (demand) and 0.998639 (supply). Besides, the estimated price elasticity is -2.408260, which is not significantly different from the elasticity value implied by the figures reported on Table 2 (which is equal to -2.478136).[10] One important difference, however, arises in the value of the conduct parameter c(10). This figure is now equal to 0.427758,

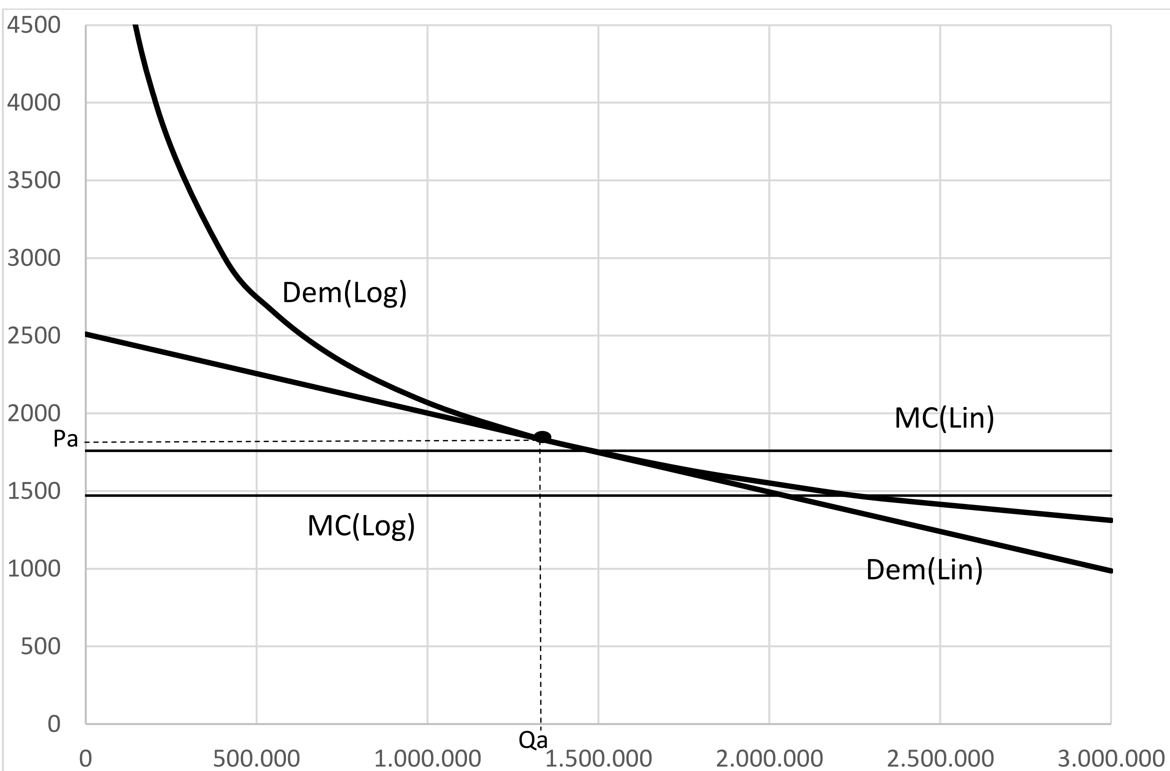
[9] This is why there is a single coefficient for LOG(PTOTAL/YNOM), instead of two separate coefficients for LOG(PTOTAL) and LOG(YNOM).

[10] This figure comes from multiplying the price coefficient of the linear regression (-1968.481) times the average price of the whole sample (which is equal to Arg$ 1789.03 per kilogram), and dividing that by the average quantity (which is equal to 1,421,096 kilograms per month).

instead of 0.041255 (which was the value reported on Table 2). That number, moreover, is now statistically different from zero at a 5% probability level (since its probability value is 0.0279).

Figure 4 depicts the estimated demand and marginal cost functions under our linear and logarithmic demand specifications. Both demand functions ("Dem(Lin)" and "Dem(Log)") are calibrated so that they pass through the point that corresponds to the average values of price and quantity in the whole sample (i.e., "Pa = 1789.03 Arg$/kg" and "Qa = 1,421,096 kg/month"). The marginal costs functions ("MC(Lin)" and "MC(Log)") are in turn associated to situations in which the conduct parameters are the ones estimated in the corresponding regressions (i.e., 0.041255 and 0.427758, respectively). As we see, this implies that the margin between Pa and MC(Lin) is much smaller than the margin between Pa and MC(Log).

4. Demand and supply under different specifications



If we now focus on the logarithmic system regressions, and we run a Wald test of the restriction "c(10) = 1", the implied probability value is 0.0028. This is once again consistent with the idea that the monopoly hypothesis is highly implausible in this case. But we can run another Wald test assuming that "c(10) = 0.394241" (which is the average value of the HHI concentration index for the whole sample). This new test generates a probability value equal to 0.8610, which is a very large number that signals that it is very likely that the market operates under some kind of "imperfect competition".

The situation in which "c(10) = HHI", moreover, is in fact a particular case of competition known as "Cournot oligopoly", which assumes that firms choose their quantities to maximize profits in response to the quantity choices of the other firms.[11] This, however, is only one of the possible equilibria that can arise under imperfect competition, and the possibilities increase in contexts in which there is product differentiation. Those contexts cannot be analyzed if we only estimate aggregate demand and supply functions, and they require the use of more complex specifications. This is what we will do in the following section, in which we will try to unravel the strategic interaction that exists between the two main firms in the Argentine chocolate bar industry (i.e., the interaction between Arcor and Mondelez).

4. Product differentiation and strategic interaction

In contexts of product differentiation, there is not a single demand function that can be used for the whole industry, but we have to consider different functions for the different goods that are supplied in that industry. Each function will relate a certain quantity with its own price, but also with the prices of the other goods that compete in the same market, generating coefficients that can be read as "own-price" elasticities and coefficients that can be read as "cross-price" elasticities.

Using the data that we have, we are able to define three different demand functions that correspond to the quantities sold by Mondelez (QMOND), Arcor (QARCOR) and the other firms (QOTHER). Under a logarithmic specification, we can write those functions in the following way:

*LOG(QMOND) = c(1) +c(2)*TREND +c(3)*WINTER +c(4)*LOG(PMOND/YNOM)*
*+C(5)*LOG(PARCOR/YNOM)*SARCOR +C(5)*LOG(POTHER/YNOM)*SOTHER*
*+C(6)*LOG(QMOND(-1))* (5) ;

[11] See Appendix 1 for an explanation of this identification between the conduct parameter and the HHI index.

*LOG(QARCOR) = c(11) +c(12)*TREND +c(3)*WINTER +C(14)*LOG(PARCOR/YNOM) +c(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(POTHER/YNOM)*SOTHER +C(6)*LOG(QARCOR(-1))* (6) ;

*LOG(QOTHER) = c(21) +c(22)*TREND +c(3)*WINTER +C(24)*LOG(POTHER/YNOM) +c(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR/YNOM)*SARCOR +C(6)*LOG(QOTHER(-1))* (7) ;

where PMOND, PARCOR and POTHER are the corresponding prices, SMOND, SARCOR and SOTHER are revenue shares, and QMOND(-1), QARCOR(-1) and QOTHER(-1) are one-period lagged quantities (i.e., quantities that correspond to the previous month).

Under this specification, coefficients c(4), c(14) and c(24) can be seen as estimates for the short-run own-price elasticities of each demand, while c(6) (which is the same coefficient in the three equations) is a measure of autocorrelation. If we divide short-run elasticities by "1-c(6)", we can obtain estimates for the long-run elasticities of demand, which we will later use to estimate price/cost margins for each firm.

Coefficient c(5), which also appears in the three demand equations, is here an estimate of the so-called "elasticity of substitution" between goods. It is a symmetric concept that tries to capture the degree of substitution between the chocolate bars manufactured by Mondelez, Arcor and the other firms. It can also be used to calculate the implicit cross-price elasticities of the whole system, that are equal to c(5) times the corresponding revenue shares (which in this system are treated as variables that change along time).[12]

In order to analyze the behavior of this market, we can include two additional equations that represent supply price functions for Arcor and Mondelez. These can be estimated using the following specification:

*PMOND = c(31) +c(32)*IPCHOC +c(33)*IPLACT +c(34)*PMHAT +c(35)*PARCOR* (8) ;

*PARCOR = c(41) +c(32)*IPCHOC +c(33)*IPLACT +c(44)*PAHAT +c(45)*PMOND* (9) ;

where PMHAT and PAHAT are artificial variables that replace PMOND and PARCOR by the fitted values of least-square regressions of those variables against a constant, TREND, WINTER and YNOM.[13]

[12] For a more complete explanation of this, see Coloma (2009).

[13] Note that we are not including a supply price function for the other firms in the industry. We are implicitly assuming that those firms have no market power, and that the relevant strategic interaction here occurs between

Once again, the first terms of these supply price equations (i.e., “c(31) +c(32)*IPCHOC +c(33)*IPLACT” and “c(41) +c(32)*IPCHOC +c(33)*IPLACT”) are estimates of marginal cost (for both Mondelez and Arcor). Conversely, the last terms (i.e., “c(34)*PMHAT +c(35)*PARCOR” and “c(44)*PAHAT +c(45)*PMOND”) are estimates of the margins between price and marginal cost. Coefficients c(34), c(35), c(44) and c(45) are in turn estimates of conduct parameters that have to do with the individual market power of the firms, and with possible coordination or collusion between those firms.[14] If those coefficients are all positive, we can infer that firms have market power, and that they exhibit some kind of (explicit or tacit) coordination to set supply prices.

If coefficients c(34) and c(44) are positive, but c(35) and c(45) are null or negative, then we can infer that firms have market power but do not behave in a cooperative or collusive fashion. Therefore, c(34) and c(44) can be compared with functions of the demand parameters that signal different types of competition between Arcor and Mondelez. In order to check that, we have performed two sets of simultaneous regressions (using three-stage least squares) for the system formed by equations 5, 6, 7, 8 and 9. The main results of those regressions are shown on Table 4.

4. Demand and supply regressions under product differentiation

Variable / Results	**General Model 1**		**General Model 2**	
	Coefficient	**Probability**	**Coefficient**	**Probability**
Demand equations				
Price elasticity Mondelez c(4)	-0.595416	0.0225	-1.009664	0.0000
Price elasticity Arcor c(14)	-0.946998	0.0001	-1.292262	0.0000
Price elasticity other firms c(24)	-0.912576	0.0002	-1.065365	0.0000
Elasticity of substitution c(5)	0.268706	0.0033	0.278797	0.0018
Autocorrelation c(6)	0.529766	0.0000	0.526567	0.0000
Supply price equations				
Chocolate price index c(32)	0.659737	0.0172	0.491678	0.0232
Milk price index c(33)	2.162377	0.0000	0.967015	0.0012
Conduct parameter c(34)	0.755413	0.0000	0.598987	0.0000
Conduct parameter c(35)	-0.624775	0.0000		
Conduct parameter c(44)	0.402993	0.0004	0.520856	0.0000
Conduct parameter c(45)	-0.266293	0.0018		

As we see, General Model 1 corresponds to a case where we have estimated the

the two main firms (i.e., between Mondelez and Arcor).

[14] For a complete explanation of the derivation of these conduct parameters, see Appendix 1.

complete model prescribed by equations 5 to 9. In General Model 2, conversely, we have eliminated coefficients c(35) and c(45), since those coefficients turned out to be negative in the estimations under General Model 1. This implies considering that there is no cooperative or collusive behavior in this industry, and that the relevant type of strategic interaction between Arcor and Mondelez has to do with some kind of competition.

The results of both sets of regressions, however, allow to discard perfect competition as a plausible scenario for this industry. This is due to the fact that coefficients c(34) and c(44) are both positive and significantly different from zero, so it is almost impossible to believe that this is an industry in which supply prices equal marginal costs (which is the main characteristic of a perfectly competitive market).

The two main models of competition that we can test are therefore related to different versions of imperfect competition, and they are known as "Bertrand (or price) competition" and "Cournot (or quantity) competition". Cournot competition is something similar to the hypothesis that we have tested in section 3, which predicted a relationship between the conduct parameter and the HHI concentration index. Under product differentiation, however, the kind of competition that arises when firms choose their quantities in response to the quantity choices of the other firms generates different results, since it is important to take into account not only the market shares of the firms but also the own-price and cross-price elasticities estimated by the model.

Supply prices under Bertrand competition, conversely, are basically dependent on the long-run own-price elasticities of each firm, and do not take into account cross-price elasticities. In our case, they imply that coefficient c(34) should be equal to "-(1-c(6))/c(4)", while coefficient c(44) should be equal to "-(1-c(6))/c(14)". This means that "c(34) = 0.468901" (instead of the estimated figure of 0.598987), while "c(44) = 0.366360" (instead of 0.520856). The differences between those numbers, however, fail to be statistically significant at any reasonable probability level. In fact, if we run a joint Wald test for the restrictions "c(34) = -(1-c(6))/c(4)" and "c(44) = -(1-c(6))/c(14)", we find that its probability value is 0.3681, which is a number that largely exceeds the 10% threshold usually employed in these cases.

But a very similar result is here obtained if we test for Cournot competition, under which it should hold that "c(34) = -c(14)*(1-c(6))/(c(4)*c(14)-c(5)^2*0.164251)" and that “c(44) = -c(4)*(1-c(6))/(c(4)*c(14)-c(5)^2*0.164251)”.[15] Indeed, the corresponding Cournot assumption implies that c(34) should be equal to 0.473535, while c(44) should be equal to 0.369980. These figures also fail to be statistically different from the estimated values of those coefficients, and the corresponding joint Wald test generates a probability value of 0.3979, which is higher than the one gotten for the case of Bertrand competition.[16]

5. Demand and supply under General Model 2

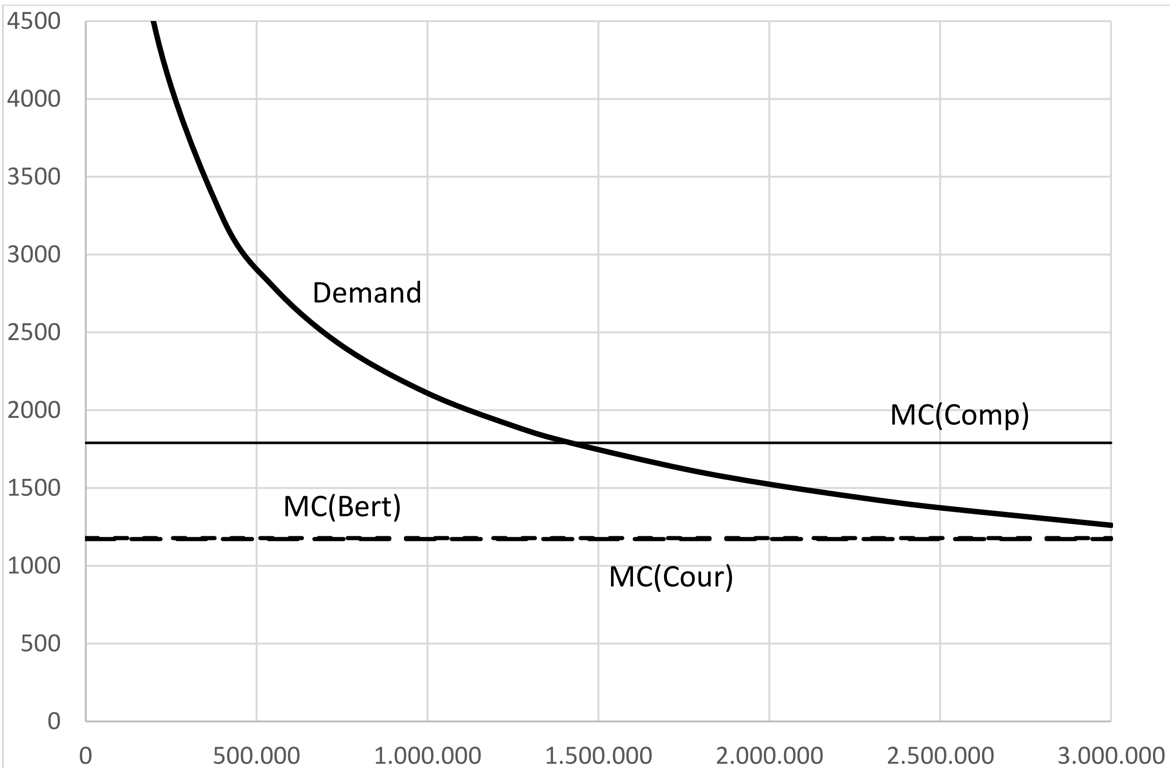


Figure 5 is a representation of the results of General Model 2, translated into a graph for total demand and average marginal cost. The line depicted as “Demand” comes from the aggregation of the logarithmic demands for QMOND, QARCOR and QOTHER, and it is calibrated so that it passes through the point that corresponds to the average values of price and total quantity. Its price elasticity is equal to -2.133244, which is the long-run figure that we obtain when we aggregate the three estimated demand functions.[17] “MC(Comp)” is

[15] The number 0.164251 that appears in these formulae is the product of the average Arcor revenue share (equal to 0.549156) times the Mondelez revenue share (equal to 0.299098).
[16] By contrast, a joint Wald test for perfect competition under this specification (i.e., a joint test of “c(34) = 0” and “c(44) = 0”) produces a probability value that is virtually equal to zero.
[17] For an explanation about the steps to calculate this, see Coloma (2023).

actually identical to the average price of the sample (equal to 1789.03 Arg$/kg), while "MC(Bert)" and "MC(Cour)" are estimates of the industry average marginal costs under the Bertrand and Cournot hypotheses (which turn out to be equal to 1178.19 Arg$/kg and to 1172.15 Arg$/kg, respectively). Note that the two lines are extremely close to one another, but they are quite different for MC(Comp) (and from the actual average price). This is due to the fact that MC(Bert) and MC(Cour) are consistent with the margins calculated under the alternative Bertrand and Cournot hypotheses.

Another way to compare the feasibility of Cournot and Bertrand competition in this case is to run two sets of regressions, imposing the restrictions mentioned in the previous paragraphs. Those sets use the same demand functions stated in equations 5, 6 and 7, and alternative sets of supply price functions. For the case of Bertrand competition, those functions are:

$$PMOND = c(31) + c(32)*IPCHOC + c(33)*IPLACT - (1-c(6)/c(4)*PMHAT \qquad (10)\ ;$$

$$PARCOR = c(41) + c(32)*IPCHOC + c(33)*IPLACT - (1-c(6)/c(14)*PAHAT \qquad (11)\ ;$$

while under Cournot competition, the corresponding supply prices can be estimated as:

$$PMOND = c(31) + c(32)*IPCHOC + c(33)*IPLACT - c(14)*(1-c(6))/(c(4)*c(14)-c(5)^2*0.164251)*PMHAT \qquad (12)\ ;$$

$$PARCOR = c(41) + c(32)*IPCHOC + c(33)*IPLACT - c(4)*(1-c(6))/(c(4)*c(14)-c(5)^2*0.164251)*PAHAT \qquad (13)\ .$$

5. Demand and supply regressions under Bertrand and Cournot competition

Variable / Results	Bertrand Model		Cournot Model	
	Coefficient	Probability	Coefficient	Probability
Demand equations				
Price elasticity Mondelez c(4)	-0.744017	0.0000	-0.747809	0.0000
Price elasticity Arcor c(14)	-0.841805	0.0000	-0.847750	0.0000
Price elasticity other firms c(24)	-1.034171	0.0000	-1.025251	0.0001
Elasticity of substitution c(5)	0.179616	0.0909	0.170198	0.1172
Autocorrelation c(6)	0.533075	0.0000	0.536448	0.0000
Supply price equations				
Chocolate price index c(32)	0.512437	0.0237	0.520855	0.0214
Milk price index c(33)	0.831548	0.0064	0.833341	0.0063

Using three-stage least squares, this leads to the results shown on Table 5. In it we see that most estimates are extremely similar. Moreover, if we reconstruct the implicit values of c(34) and c(44) provided by these estimations, we see that they are almost identical. The Bertrand model estimation produces "c(34) = -(1-c(6)/c(4) = 0.627573" and "c(44) = -(1-c(6)/c(14) = 0.554671", while the Cournot model implies "c(34) = -c(14)*(1-c(6))/(c(4)*c(14)-c(5)^2*0.164251) = 0.624569" and "c(44) = -c(4)*(1-c(6))/(c(4)*c(14)-c(5)^2*0.164251) = 0.550938".

The goodness of fit of both estimations (measured by the corresponding R^2 coefficients) is also remarkably similar. The Bertrand model is slightly better than the Cournot model in the estimation of the Mondelez demand and the Mondelez supply price functions, and slightly worse in the estimation of the Arcor demand, the other firms' demand and the Arcor supply price.[18]

An alternative to evaluate the relative performance of the Bertrand and Cournot models is to run a couple of "J-tests" for non-nested hypotheses, that try to see if the predicted values of one model are able to improve the estimations under the other model.[19] In our case, this can be done by running a set of regressions formed by equations 5, 6 and 7, together with two equations of the following form:

*PMOND = c(31) +c(32)*IPCHOC +c(33)*IPLACT –(1-c(6)/c(4)*PMHAT +c(36)*(PMCFIT-PMBFIT)* (14) ;

*PARCOR = c(41) +c(32)*IPCHOC +c(33)*IPLACT –(1-c(6)/c(14)*PAHAT +c(36)*(PACFIT-PABFIT)* (15) ;

where PMCFIT and PACFIT are the fitted values for PMOND and PARCOR under the Cournot model, while PMBFIT and PABFIT are the fitted values for PMOND and PARCOR under the Bertrand model. In this specification, coefficient c(36) measures the relative ability of the Cournot model (i.e., of the estimates of that model) to improve the results obtained under the Bertrand model. Alternatively, we can also run another set of regressions formed by equations 5, 6 and 7, together with these two equations:

*PMOND = c(31) +c(32)*IPCHOC +c(33)*IPLACT –c(14)*(1-c(6))/(c(4)*c(14)-c(5)*^{2}**0.164251)*PMHAT +c(36)*(PMBFIT-PMCFIT)* (16) ;

*PARCOR = c(41) +c(32)*IPCHOC +c(33)*IPLACT –c(4)*(1-c(6))/(c(4)*c(14)-c(5)*^{2}**0.164251)*PAHAT +c(36)*(PABFIT-PACFIT)* (17) ;

[18] See Appendix 2.
[19] For other alternative ways to test non-nested hypotheses, see Pesaran (2015), chapter 11.

in which c(36) measures the relative ability of the Bertrand model to improve the results obtained under the Cournot model.

Under the regressions of the system formed by equations 14 and 15, the value of c(36) is estimated as equal to -41.61307, while, under the regressions of the system formed by equations 16 and 17, it is equal to 40.48812. Both coefficients fail to be significantly different from zero, since their corresponding probability values are 0.1661 and 0.1827. As the first of those values is smaller than the second value, however, we can say that the Cournot model is slightly better than the Bertrand model to improve the estimates of its alternative counterpart.

5. Concluding remarks

After all the analyses performed with data from the Argentine chocolate bar industry during the period 2019-2022, we can basically conclude that such industry seems to operate under a regime of competition that could be close to both the Bertrand model (i.e., price competition) and the Cournot model (i.e., quantity competition). When we introduce the possible existence of product differentiation (implied by the distinction between the chocolate brands sold by Arcor, Mondelez, and the other firms in the market), we can discard extreme pricing behaviors such as perfect competition and collusion, but we cannot clearly distinguish between alternative models of imperfect competition.

The Argentine chocolate bar industry is characterized by a relatively high supply concentration (since its main supplier has a revenue share around 55%, and the second largest supplier has a revenue share around 30%). This does not mean, however, that the largest firm (Arcor) has more market power than the second one (Mondelez). As we see that the average Mondelez prices are higher than the average Arcor prices (at least during the period under analysis), there is a chance that the first of those firms has more market power than the second one, due to the existence of product differentiation.

This possibility is confirmed in our analysis when we observe that, in all our alternative estimations, the Mondelez demand function appears to be more inelastic than the Arcor demand function, and this is a key to obtain a result under which it is more likely that Mondelez price/cost margins are higher than Arcor price/cost margins. This is indeed what we get when we estimate coefficients c(34) and c(44) in a model that nests all types of competition (General Model 2), for which we obtain a relative margin of 0.598987 for Mondelez and a relative margin of 0.520856 for Arcor.[20] Similar results appear when we restrict our estimations to alternative non-nested cases of price competition (Bertrand) and quantity competition (Cournot).

The introduction of product differentiation also helps to avoid some conclusions that appear in the demand-and-supply specifications that ignore that characteristic. For example, when we estimated a model with a linear demand function for the whole Argentine chocolate bar industry, we obtained a conduct parameter that was consistent with perfect competition instead of imperfect competition. This identification disappears if we use a logarithmic demand, but that model still ignores the fact that strategic interaction in this industry occurs mainly between two firms that supply idiosyncratically differentiated products.

The single-demand approach is also unable to distinguish between imperfect competition and "imperfect collusion". For example, when we estimated a conduct parameter "c(10) = 0.427758" in our logarithmic specification of section 3, we could not discard that such coefficient had been generated by a process in which firms cooperated to increase prices above the competitive level but below the monopoly one. When we introduced product differentiation and demands at the level of the firms, conversely, we had separate conduct parameters for individual market power (c(34) and c(44)) and for joint market power (c(35) and c(45)). As the last set of parameters turned out to be negative, we could safely reject the collusive hypothesis, and focused on analyzing alternative competitive hypotheses (i.e., the Bertrand and Cournot models).[21]

Our comparison between the Bertrand and Cournot models is in this case not conclusive, but it shows a slight preference for the Cournot hypothesis. This is because, in General Model 2, it is a bit more likely that the conduct parameter coefficients are equal to the predicted Cournot values, and the Cournot model also generates a better J-test statistic when its fitted values are introduced into the Bertrand model.

[20] These numbers can be interpreted as estimates of the ratio between price minus marginal cost and price itself ($(P_i-MC_i)/P_i$), also known as "Lerner index". They imply that Mondelez's marginal profit would be equivalent to 59.90% of its price, and that Arcor's marginal profit would be equivalent to 52.09% of its price.

[21] This is actually a way to overcome one of the main critiques to the conduct parameter approach, originally stated by Corts (1999). For other alternatives to deal with the Corts critique, see Reiss and Wolak (2007) and Puller (2009).

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Appendix 1. Derivation of conduct parameter values

The bulk of the analysis that was performed in this paper has to do with the estimation of conduct parameters for the Argentine chocolate bar industry under different assumptions. In this appendix we will derive the main formulae used to compute those parameters.

The first conduct parameter that we calculated was the one corresponding to the context of a single linear demand. Let us assume that demand has the following form:

$$Q = a + b \cdot P + g \cdot Y \qquad \text{(A1) ;}$$

and each individual firm in the industry seeks to maximize the following profit function:

$$\Pi_i = (P - c) \cdot Q_i \qquad \text{(A2) ;}$$

where P is price, Q is total quantity, Q_i is individual quantity, Y is nominal income, and a, b, g and c are parameters. Under perfect competition, each firm will maximize profits choosing Q_i and taking P as given, and that will generate the following first-order condition:

$$\frac{\partial \Pi_i}{\partial Q_i} = P - c = 0 \qquad \rightarrow \qquad P = c \qquad \text{(A3) .}$$

Conversely, in a monopoly situation, the corresponding first-order condition will be:

$$\frac{\partial \Pi_i}{\partial Q} = P + \frac{\partial P}{\partial Q} \cdot Q - c = 0 \qquad \rightarrow \qquad P = c - \frac{\partial P}{\partial Q} \cdot Q = c - \frac{1}{b} \cdot Q \qquad \text{(A4) ;}$$

while under Cournot competition we will have that:

$$\frac{\partial \Pi_i}{\partial Q_i} = P + \frac{\partial P}{\partial Q} \cdot Q_i - c = 0 \qquad \rightarrow \qquad P = c - \frac{\partial P}{\partial Q} \cdot Q_i = c - \frac{1}{b} \cdot Q_i \qquad \text{(A5) .}$$

On average, this last equation can be written as:

$$P = c - \frac{1}{b} \cdot \sum s_i \cdot Q_i = c - \frac{1}{b} \cdot \sum s_i \cdot s_i \cdot Q = c - \frac{\sum {s_i}^2}{b} \cdot Q = c - \frac{HHI}{b} \cdot Q \qquad \text{(A6) ;}$$

where s_i is the market share of the individual firm, and *HHI* is the Herfindahl-Hirschman index. As we can see, equations A3, A4 and A6 can all be nested into the following formulation:

$$P = c - \frac{\theta}{b} \cdot Q \qquad \text{(A7) ;}$$

where θ is a conduct parameter whose value should be equal to zero under perfect competition, equal to one under monopoly, and equal to *HHI* under Cournot oligopoly. In the econometric model shown on section 3, the conduct parameter θ was estimated by coefficient c(10), while the demand parameter b was estimated by coefficient c(4).

If, instead of having a linear demand, we have a power function demand of the following form:

$$Q = A \cdot P^{\alpha} \cdot Y^{\lambda} \qquad \text{(A8) ;}$$

where A, α and λ are parameters, then we can rewrite this demand function using a logarithmic transformation under which it holds that:

$$\log(Q) = \log(A) + \alpha \cdot \log(P) + \lambda \cdot \log(Y) \qquad \text{(A9) ;}$$

where *log* is the natural logarithm of the corresponding variable or parameter. If this function is homogeneous of degree zero, then it will hold that "$\alpha + \lambda = 0$", and we can therefore write:

$$\log(Q) = \log(A) + \alpha \cdot \log(P) - \alpha \cdot \log(Y) = \log(A) + \alpha \cdot \log(P/Y) \qquad \text{(A10) .}$$

With this change in demand, the profit-maximizing decision of a perfectly competitive firm will still be equal to the one prescribed by Equation A3, but the first-order condition of a monopolist would in turn become:

$$\frac{\partial \Pi_i}{\partial Q} = P + \frac{\partial P}{\partial Q} \cdot Q - c = 0 \qquad \rightarrow \qquad P = c - \frac{\partial P}{\partial Q} \cdot \frac{Q}{P} \cdot P = c - \frac{1}{\alpha} \cdot P \qquad \text{(A11) ;}$$

while on average, for a Cournot oligopoly, it will hold that:

$$P = c - \frac{HHI}{\alpha} \cdot P \qquad \text{(A12) .}$$

Once again, all these equations can be nested into a general model for which it will hold that:

$$P = c - \frac{\theta}{\alpha} \cdot P \qquad \text{(A13) ;}$$

where θ is a conduct parameter whose value is "$\theta = 0$" under perfect competition, "$\theta = 1$" under monopoly, and "$\theta = HHI$" under Cournot oligopoly. In the logarithmic-demand model shown on section 3, the conduct parameter θ was estimated by coefficient c(10), while the elasticity parameter α was estimated by coefficient c(4).

Let us now assume that this industry has two main firms (1 and 2) that operate in a context of product differentiation, and that their demands are:

$$Q_1 = A \cdot P_1^{\alpha} \cdot P_2^{\beta} \cdot Y^{-\alpha-\beta} \cdot Q_{1(-1)}{}^{\rho} \ ; \qquad Q_2 = B \cdot P_1^{\gamma} \cdot P_2^{\delta} \cdot Y^{-\gamma-\delta} \cdot Q_{2(-1)}{}^{\rho} \qquad \text{(A14) ;}$$

where P_1 and P_2 are prices, Q_1 and Q_2 are quantities, $Q_{1(-1)}$ and $Q_{2(-1)}$ are lagged quantities (i.e., the quantities corresponding to the previous period), and $A, B, \alpha, \beta, \gamma, \delta$ and ρ are parameters.[22] Given that, the corresponding logarithmic transformations are:

$$\log(Q_1) = \log(A) + \alpha \cdot \log(P_1/Y) + \beta \cdot \log(P_2/Y) + \rho \cdot \log(Q_{1(-1)}) \qquad \text{(A15) ;}$$

$$\log(Q_2) = \log(B) + \gamma \cdot \log(P_1/Y) + \delta \cdot \log(P_2/Y) + \rho \cdot \log(Q_{2(-1)}) \qquad \text{(A16) ;}$$

and, in a long-run steady-state context where "$Q_1 = Q_{1(-1)}$" and "$Q_2 = Q_{2(-1)}$", it will hold that:

$$\log(Q_1) = \frac{\log(A)}{1-\rho} + \frac{\alpha}{1-\rho} \cdot \log(P_1/Y) + \frac{\beta}{1-\rho} \cdot \log(P_2/Y) \qquad \text{(A17) ;}$$

[22] For an alternative derivation of this, using linear demands instead of power functions, see Davis and Garcés (2010), chapter 6.

$$\log(Q_2) = \frac{\log(B)}{1-\rho} + \frac{\gamma}{1-\rho} \cdot \log(P_1 / Y) + \frac{\delta}{1-\rho} \cdot \log(P_2 / Y) \qquad \text{(A18)} .$$

If this market operates under perfect competition, then each firm will maximize profits taking prices as given, and their corresponding first-order conditions will be:

$$\frac{\partial \Pi_1}{\partial Q_1} = P_1 - c_1 = 0 \;\; \rightarrow \;\; P_1 = c_1 \;\; ; \qquad \frac{\partial \Pi_2}{\partial Q_2} = P_2 - c_2 = 0 \;\; \rightarrow \;\; P_2 = c_2 \qquad \text{(A19)} .$$

Conversely, if each firm chooses its price, taking the other firm's price as given (Bertrand competition), it will hold that:

$$\frac{\partial \Pi_1}{\partial P_1} = Q_1 + (P_1 - c_1) \cdot \frac{\partial Q_1}{\partial P_1} = 0 \quad \rightarrow \quad P_1 = c_1 - \frac{\partial P_1}{\partial Q_1} \cdot \frac{Q_1}{P_1} \cdot P_1 = c_1 - \frac{1-\rho}{\alpha} \cdot P_1 \qquad \text{(A20)} ;$$

$$\frac{\partial \Pi_2}{\partial P_2} = Q_2 + (P_2 - c_2) \cdot \frac{\partial Q_2}{\partial P_2} = 0 \quad \rightarrow \quad P_2 = c_2 - \frac{\partial P_2}{\partial Q_2} \cdot \frac{Q_2}{P_2} \cdot P_2 = c_2 - \frac{1-\rho}{\delta} \cdot P_2 \qquad \text{(A21)} .$$

Another possible type of competition is Cournot oligopoly with differentiated products, in which each firm chooses its quantity, taking the other firm's quantity as given. In order to model this, it is necessary to transform the demand functions into demand price functions, which in this case will be something like the following:

$$P_1 = C \cdot Q_1^{\frac{\delta}{\alpha \cdot \delta - \beta \cdot \gamma}} \cdot Q_2^{\frac{-\beta}{\alpha \cdot \delta - \beta \cdot \gamma}} \cdot Y^{\frac{\beta - \delta}{\alpha \cdot \delta - \beta \cdot \gamma}} \cdot P_{1(-1)}{}^{\rho} \qquad \text{(A22)} ;$$

$$P_2 = D \cdot Q_1^{\frac{-\gamma}{\alpha \cdot \delta - \beta \cdot \gamma}} \cdot Q_2^{\frac{\alpha}{\alpha \cdot \delta - \beta \cdot \gamma}} \cdot Y^{\frac{\gamma - \alpha}{\alpha \cdot \delta - \beta \cdot \gamma}} \cdot P_{2(-1)}{}^{\rho} \qquad \text{(A23)} ;$$

and the corresponding first-order conditions will imply:

$$\frac{\partial \Pi_1}{\partial Q_1} = P_1 + \frac{\partial P_1}{\partial Q_1} \cdot Q_1 - c_1 = 0 \quad \rightarrow \quad P_1 = c_1 - \frac{\partial P_1}{\partial Q_1} \cdot \frac{Q_1}{P_1} \cdot P_1 = c_1 - \frac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \beta \cdot \gamma} \cdot P_1 \qquad \text{(A24)} ;$$

$$\frac{\partial \Pi_2}{\partial Q_2} = P_2 + \frac{\partial P_2}{\partial Q_2} \cdot Q_2 - c_2 = 0 \quad \rightarrow \quad P_2 = c_2 - \frac{\partial P_2}{\partial Q_2} \cdot \frac{Q_2}{P_2} \cdot P_2 = c_2 - \frac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \beta \cdot \gamma} \cdot P_2 \qquad \text{(A25)} .$$

If we introduce symmetry restrictions into the system specification, one possible alternative is to define a substitution elasticity parameter (σ) whose relationship with the other parameters is the following:

$$\beta = \sigma \cdot s_2 \qquad ; \qquad \gamma = \sigma \cdot s_1 \qquad \text{(A26)} ;$$

where s_1 and s_2 are the revenue market shares of firms 1 and 2. This implies that equations A24 and A25 now become:

$$P_1 = c_1 - \frac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2} \cdot P_1 ; \qquad P_2 = c_2 - \frac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2} \cdot P_2 \qquad \text{(A27)} ;$$

A last type of strategic interaction between firms is the one that supposes the existence of collusion, that can be modeled as a situation in which both firms maximize their joint profits. This implies the following first-order conditions:

$$\frac{\partial \Pi_{1+2}}{\partial Q_1} = P_1 + \frac{\partial P_1}{\partial Q_1} \cdot Q_1 - c_1 + \frac{\partial P_2}{\partial Q_1} \cdot Q_2 = 0 \qquad \rightarrow$$

$$P_1 = c_1 - \frac{\partial P_1}{\partial Q_1} \cdot \frac{Q_1}{P_1} \cdot P_1 - \frac{\partial P_2}{\partial Q_1} \cdot \frac{Q_2}{Q_1} \cdot \frac{Q_1}{P_2} \cdot P_2 = c_1 - \frac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \beta \cdot \gamma} \cdot P_1 + \frac{\gamma \cdot (1-\rho)}{\alpha \cdot \delta - \beta \cdot \gamma} \cdot \frac{s_2}{s_1} \cdot P_2 \qquad \rightarrow$$

$$P_1 = c_1 - \frac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2} \cdot P_1 + \frac{\sigma \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2} \cdot s_2 \cdot P_2 \qquad \text{(A28) ;}$$

$$\frac{\partial \Pi_{1+2}}{\partial Q_2} = P_2 + \frac{\partial P_2}{\partial Q_2} \cdot Q_2 - c_2 + \frac{\partial P_1}{\partial Q_2} \cdot Q_1 = 0 \qquad \rightarrow$$

$$P_2 = c_2 - \frac{\partial P_2}{\partial Q_2} \cdot \frac{Q_2}{P_2} \cdot P_2 - \frac{\partial P_1}{\partial Q_2} \cdot \frac{Q_1}{Q_2} \cdot \frac{Q_2}{P_1} \cdot P_1 = c_2 - \frac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \beta \cdot \gamma} \cdot P_2 + \frac{\beta \cdot (1-\rho)}{\alpha \cdot \delta - \beta \cdot \gamma} \cdot \frac{s_1}{s_2} \cdot P_1 \qquad \rightarrow$$

$$P_2 = c_2 - \frac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2} \cdot P_2 + \frac{\sigma \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2} \cdot s_1 \cdot P_1 \qquad \text{(A29) .}$$

The four models described can in turn be nested into a single model that can be written in the following way:

$$P_1 = c_1 + \theta_A \cdot P_1 + \theta_B \cdot P_2 \quad ; \quad P_2 = c_2 + \theta_C \cdot P_2 + \theta_D \cdot P_1 \qquad \text{(A30) ;}$$

and each of the competing hypothesis become:

Perfect competition: $\theta_A = 0$; $\theta_B = 0$; $\theta_C = 0$; $\theta_D = 0$ (A31) ;

Bertrand competition: $\theta_A = -\frac{1-\rho}{\alpha}$; $\theta_B = 0$; $\theta_C = -\frac{1-\rho}{\delta}$; $\theta_D = 0$ (A32) ;

Cournot competition: $\theta_A = -\frac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$; $\theta_B = 0$;

$\theta_C = -\frac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$; $\theta_D = 0$ (A33) ;

Collusion: $\theta_A = -\frac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$; $\theta_B = \frac{\sigma \cdot (1-\rho) \cdot s_2}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$;

$\theta_C = -\frac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$; $\theta_D = \frac{\sigma \cdot (1-\rho) \cdot s_1}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$ (A34) .

If we discard collusion as a possible outcome (e.g., because the estimated coefficients for θ_B and θ_D are both negative instead of positive), then the three remaining hypotheses can be tested using a more simplified model of this type:

$$P_1 = c_1 + \theta_A \cdot P_1 \quad ; \quad P_2 = c_2 + \theta_C \cdot P_2 \qquad \text{(A35) ;}$$

under which the alternative hypotheses can be written as:

Perfect competition: $\theta_A = 0$; $\theta_C = 0$ (A36) ;

Bertrand competition: $\theta_A = -\dfrac{1-\rho}{\alpha}$; $\theta_C = -\dfrac{1-\rho}{\delta}$ (A37) ;

Cournot competition: $\theta_A = -\dfrac{\delta \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$; $\theta_C = -\dfrac{\alpha \cdot (1-\rho)}{\alpha \cdot \delta - \sigma^2 \cdot s_1 \cdot s_2}$ (A38) .

These are actually the models that we have tested in section 4, both as nested hypotheses and also as non-nested ones. In that section, parameter α was estimated by coefficient c(4), parameter σ was estimated by coefficient c(5), parameter ρ was estimated by coefficient c(6), and parameter δ was estimated by coefficient c(14). Conduct parameters θ_A, θ_B, θ_C and θ_D, in turn, were estimated by coefficients c(34), c(35), c(44) and c(45).

Appendix 2. Complete estimation results

System: LINEARDEMAND
Estimation Method: Three-Stage Least Squares
Date: 05/12/24 Time: 00:26
Sample: 1 48
Included observations: 48
Total system (balanced) observations 96
Iterate coefficients after one-step weighting matrix
Convergence achieved after: 1 weight matrix, 6 total coef iterations

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	1064613.	155255.9	6.857146	0.0000
C(2)	9666.681	9025.509	1.071040	0.2871
C(3)	805810.5	90562.21	8.897867	0.0000
C(4)	-1968.481	645.2246	-3.050846	0.0030
C(5)	49.51725	13.62422	3.634500	0.0005
C(7)	-202.7624	18.62655	-10.88567	0.0000
C(8)	0.245525	0.181288	1.354337	0.1791
C(9)	2.871870	0.218144	13.16504	0.0000
C(10)	0.041255	0.032599	1.265555	0.2091
Determinant residual covariance		1.27E+14		

Equation: QTOTAL = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*PTOTAL +C(5)*YNOM
Instruments: TREND WINTER YNOM IPCHOC IPLACT C
Observations: 48

R-squared	0.736759	Mean dependent var	1421096.
Adjusted R-squared	0.712272	S.D. dependent var	573262.6
S.E. of regression	307499.9	Sum squared resid	4.07E+12
Durbin-Watson stat	1.326545		

Equation: PTOTAL = C(7) +C(8)*IPCHOC +C(9)*IPLACT -C(10)/C(4)
*QTOTAL
Instruments: TREND WINTER YNOM IPCHOC IPLACT C
Observations: 48

R-squared	0.998016	Mean dependent var	1789.028
Adjusted R-squared	0.997831	S.D. dependent var	910.5934
S.E. of regression	42.40627	Sum squared resid	77326.55
Durbin-Watson stat	0.818759		

System: LOGDEMAND
Estimation Method: Three-Stage Least Squares
Date: 05/14/24   Time: 19:10
Sample: 1 48
Included observations: 48
Total system (balanced) observations 96
Iterate coefficients after one-step weighting matrix
Convergence achieved after: 1 weight matrix, 5 total coef iterations

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	5.118936	1.910314	2.679631	0.0088
C(2)	0.003635	0.003079	1.180609	0.2409
C(3)	0.565893	0.068238	8.292909	0.0000
C(4)	-2.408260	0.542196	-4.441674	0.0000
C(7)	-161.2958	18.02152	-8.950175	0.0000
C(8)	0.107897	0.143147	0.753749	0.4530
C(9)	2.492638	0.244852	10.18016	0.0000
C(10)	0.427758	0.191383	2.235082	0.0279
Determinant residual covariance		54.08093		

Equation: LOG(QTOTAL) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PTOTAL/YNOM)
Instruments: TREND WINTER LOG(YNOM) IPCHOC IPLACT C
Observations: 48

R-squared	0.701003	Mean dependent var	14.08666
Adjusted R-squared	0.680617	S.D. dependent var	0.409506
S.E. of regression	0.231428	Sum squared resid	2.356594
Durbin-Watson stat	1.146428		

Equation: PTOTAL = C(7) +C(8)*IPCHOC +C(9)*IPLACT -C(10)/C(4)
*PTHAT
Instruments: TREND WINTER LOG(YNOM) IPCHOC IPLACT C
Observations: 48

R-squared	0.998639	Mean dependent var	1789.028
Adjusted R-squared	0.998512	S.D. dependent var	910.5934
S.E. of regression	35.12547	Sum squared resid	53053.33
Durbin-Watson stat	1.074771		

System: GENERALMODEL1
Estimation Method: Three-Stage Least Squares
Date: 05/15/24 Time: 13:51
Sample: 2 48
Included observations: 47
Total system (balanced) observations 235
Linear estimation after one-step weighting matrix

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	4.435454	1.108856	4.000026	0.0001
C(2)	0.003393	0.002381	1.424676	0.1557
C(3)	0.302506	0.040712	7.430290	0.0000
C(4)	-0.595416	0.259084	-2.298153	0.0225
C(5)	0.268706	0.090559	2.967188	0.0033
C(6)	0.529766	0.052426	10.10502	0.0000
C(11)	3.178972	0.950312	3.345187	0.0010
C(12)	0.002189	0.002030	1.078583	0.2820
C(14)	-0.946998	0.236711	-4.000645	0.0001
C(21)	3.046394	0.826068	3.687825	0.0003
C(22)	0.003403	0.002784	1.222218	0.2230
C(24)	-0.912576	0.244244	-3.736325	0.0002
C(31)	-207.0325	39.57768	-5.231042	0.0000
C(32)	0.659737	0.274674	2.401893	0.0172
C(33)	2.162377	0.359502	6.014927	0.0000
C(34)	0.755413	0.093161	8.108651	0.0000
C(35)	-0.624775	0.093524	-6.680375	0.0000
C(41)	-207.4006	30.44894	-6.811423	0.0000
C(44)	0.402993	0.111814	3.604139	0.0004
C(45)	-0.266293	0.084315	-3.158298	0.0018
Determinant residual covariance		6.410445		

Equation: LOG(QMOND) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PMOND/YNOM) +C(5)*LOG(PARCOR/YNOM)*SARCOR
+C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)*LOG(QMOND(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.780549	Mean dependent var	12.73075
Adjusted R-squared	0.753786	S.D. dependent var	0.422652
S.E. of regression	0.209719	Sum squared resid	1.803272
Durbin-Watson stat	0.928286		

Equation: LOG(QARCOR) = C(11) +C(12)*TREND +C(3)* WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(14)*LOG(PARCOR
/YNOM) +C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)
*LOG(QARCOR(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.817000	Mean dependent var	13.54470
Adjusted R-squared	0.794683	S.D. dependent var	0.375930
S.E. of regression	0.170341	Sum squared resid	1.189662
Durbin-Watson stat	1.249317		

Equation: LOG(QOTROS) = C(21) +C(22)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR
/YNOM)*SARCOR +C(24)*LOG(POTROS/YNOM) +C(6)
*LOG(QOTROS(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.941155	Mean dependent var	12.25063
Adjusted R-squared	0.933978	S.D. dependent var	0.613384
S.E. of regression	0.157607	Sum squared resid	1.018437
Durbin-Watson stat	1.288143		

Equation: PMOND = C(31) +C(32)*IPCHOC +C(33)*IPLACT +C(34)
*PMHAT +C(35)*PARCOR
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.992067	Mean dependent var	2150.733
Adjusted R-squared	0.991311	S.D. dependent var	1101.750
S.E. of regression	102.6975	Sum squared resid	442965.0
Durbin-Watson stat	0.796040		

Equation: PARCOR = C(41) +C(32)*IPCHOC +C(33)*IPLACT +C(44)
*PAHAT +C(45)*PMOND
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.996303	Mean dependent var	1737.188
Adjusted R-squared	0.995951	S.D. dependent var	904.6201
S.E. of regression	57.56048	Sum squared resid	139154.8
Durbin-Watson stat	0.953911		

System: GENERALMODEL2
Estimation Method: Three-Stage Least Squares
Date: 05/15/24 Time: 13:52
Sample: 2 48
Included observations: 47
Total system (balanced) observations 235
Linear estimation after one-step weighting matrix

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.119514	0.969652	3.217147	0.0015
C(2)	0.001678	0.002333	0.719113	0.4728
C(3)	0.287247	0.041282	6.958223	0.0000
C(4)	-1.009664	0.217727	-4.637292	0.0000
C(5)	0.278797	0.087983	3.168756	0.0018
C(6)	0.526567	0.052650	10.00124	0.0000
C(11)	2.015282	0.914068	2.204739	0.0285
C(12)	0.000796	0.002007	0.396668	0.6920
C(14)	-1.292262	0.222240	-5.814718	0.0000
C(21)	2.613759	0.820498	3.185576	0.0017
C(22)	0.001258	0.002764	0.454966	0.6496
C(24)	-1.065365	0.242240	-4.397965	0.0000
C(31)	-84.37206	36.44034	-2.315348	0.0215
C(32)	0.491678	0.215038	2.286474	0.0232
C(33)	0.967015	0.295036	3.277615	0.0012
C(34)	0.598987	0.073187	8.184364	0.0000
C(41)	-113.5237	31.08714	-3.651789	0.0003
C(44)	0.520856	0.087661	5.941736	0.0000
Determinant residual covariance		13.61257		

Equation: LOG(QMOND) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PMOND/YNOM) +C(5)*LOG(PARCOR/YNOM)*SARCOR
+C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)*LOG(QMOND(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.766295	Mean dependent var	12.73075
Adjusted R-squared	0.737795	S.D. dependent var	0.422652
S.E. of regression	0.216423	Sum squared resid	1.920396
Durbin-Watson stat	0.824448		

Equation: LOG(QARCOR) = C(11) +C(12)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(14)*LOG(PARCOR
/YNOM) +C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)
*LOG(QARCOR(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.829225	Mean dependent var	13.54470
Adjusted R-squared	0.808399	S.D. dependent var	0.375930
S.E. of regression	0.164553	Sum squared resid	1.110186
Durbin-Watson stat	1.219561		

Equation: LOG(QOTROS) = C(21) +C(22)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR
/YNOM)*SARCOR +C(24)*LOG(POTROS/YNOM) +C(6)
*LOG(QOTROS(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.943921	Mean dependent var	12.25063
Adjusted R-squared	0.937082	S.D. dependent var	0.613384
S.E. of regression	0.153858	Sum squared resid	0.970563
Durbin-Watson stat	1.259514		

Equation: PMOND = C(31) +C(32)*IPCHOC +C(33)*IPLACT +C(34)
*PMHAT
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.991646	Mean dependent var	2150.733
Adjusted R-squared	0.991064	S.D. dependent var	1101.750
S.E. of regression	104.1510	Sum squared resid	466439.8
Durbin-Watson stat	0.596214		

Equation: PARCOR = C(41) +C(32)*IPCHOC +C(33)*IPLACT +C(44)
*PAHAT
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.994915	Mean dependent var	1737.188
Adjusted R-squared	0.994560	S.D. dependent var	904.6201
S.E. of regression	66.72305	Sum squared resid	191434.5
Durbin-Watson stat	0.670573		

System: BERTRANDMODEL
Estimation Method: Three-Stage Least Squares
Date: 05/15/24 Time: 13:55
Sample: 2 48
Included observations: 47
Total system (balanced) observations 235
Iterate coefficients after one-step weighting matrix
Convergence achieved after: 1 weight matrix, 9 total coef iterations

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.702003	0.624062	5.932110	0.0000
C(2)	0.001548	0.002315	0.668679	0.5044
C(3)	0.288663	0.041008	7.039271	0.0000
C(4)	-0.744017	0.109995	-6.764076	0.0000
C(5)	0.179616	0.105776	1.698074	0.0909
C(6)	0.533075	0.053607	9.944124	0.0000
C(11)	3.415633	0.663309	5.149385	0.0000
C(12)	0.000830	0.002098	0.395442	0.6929
C(14)	-0.841805	0.147145	-5.720928	0.0000
C(21)	2.327810	0.805949	2.888285	0.0043
C(22)	0.002012	0.002792	0.720442	0.4720
C(24)	-1.034171	0.248359	-4.164019	0.0000
C(31)	-74.12201	36.56317	-2.027231	0.0439
C(32)	0.512437	0.224924	2.278267	0.0237
C(33)	0.831548	0.301973	2.753717	0.0064
C(41)	-100.4885	31.07180	-3.234075	0.0014

Determinant residual covariance		23.05681		

Equation: LOG(QMOND) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PMOND/YNOM) +C(5)*LOG(PARCOR/YNOM)*SARCOR
+C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)*LOG(QMOND(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.771569	Mean dependent var	12.73075
Adjusted R-squared	0.743712	S.D. dependent var	0.422652
S.E. of regression	0.213967	Sum squared resid	1.877058
Durbin-Watson stat	0.857252		

Equation: LOG(QARCOR) = C(11) +C(12)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(14)*LOG(PARCOR
/YNOM) +C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)
*LOG(QARCOR(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.811698	Mean dependent var	13.54470
Adjusted R-squared	0.788734	S.D. dependent var	0.375930
S.E. of regression	0.172791	Sum squared resid	1.224133
Durbin-Watson stat	1.226593		

Equation: LOG(QOTROS) = C(21) +C(22)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR
/YNOM)*SARCOR +C(24)*LOG(POTROS/YNOM) +C(6)
*LOG(QOTROS(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.944758	Mean dependent var	12.25063
Adjusted R-squared	0.938021	S.D. dependent var	0.613384
S.E. of regression	0.152705	Sum squared resid	0.956072
Durbin-Watson stat	1.293175		

Equation: PMOND = C(31) +C(32)*IPCHOC +C(33)*IPLACT -(1-C(6))
/C(4)*PMHAT
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.991848	Mean dependent var	2150.733
Adjusted R-squared	0.991072	S.D. dependent var	1101.750
S.E. of regression	104.1048	Sum squared resid	455188.0
Durbin-Watson stat	0.617429		

Equation: PARCOR = C(41) +C(32)*IPCHOC +C(33)*IPLACT -(1-C(6))
/C(14)*PAHAT
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.994646	Mean dependent var	1737.188
Adjusted R-squared	0.994137	S.D. dependent var	904.6201
S.E. of regression	69.26896	Sum squared resid	201523.9
Durbin-Watson stat	0.670460		

System: COURNOTMODEL
Estimation Method: Three-Stage Least Squares
Date: 05/15/24 Time: 13:55
Sample: 2 48
Included observations: 47
Total system (balanced) observations 235
Iterate coefficients after one-step weighting matrix
Convergence achieved after: 1 weight matrix, 11 total coef iterations

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.624524	0.612443	5.918135	0.0000
C(2)	0.001461	0.002328	0.627300	0.5311
C(3)	0.287046	0.040940	7.011379	0.0000
C(4)	-0.747809	0.111718	-6.693721	0.0000
C(5)	0.170198	0.108220	1.572698	0.1172
C(6)	0.536448	0.053664	9.996499	0.0000
C(11)	3.336834	0.655288	5.092165	0.0000
C(12)	0.000707	0.002106	0.335722	0.7374
C(14)	-0.847750	0.149387	-5.674860	0.0000
C(21)	2.290292	0.810349	2.826303	0.0051
C(22)	0.002049	0.002823	0.725854	0.4687
C(24)	-1.025251	0.251239	-4.080777	0.0001
C(31)	-74.49661	36.57054	-2.037066	0.0428
C(32)	0.520855	0.224747	2.317518	0.0214
C(33)	0.833341	0.302389	2.755857	0.0063
C(41)	-100.8452	31.13293	-3.239180	0.0014
Determinant residual covariance		24.10472		

Equation: LOG(QMOND) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PMOND/YNOM) +C(5)*LOG(PARCOR/YNOM)*SARCOR
+C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)*LOG(QMOND(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.771228	Mean dependent var	12.73075
Adjusted R-squared	0.743329	S.D. dependent var	0.422652
S.E. of regression	0.214127	Sum squared resid	1.879859
Durbin-Watson stat	0.854255		

Equation: LOG(QARCOR) = C(11) +C(12)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(14)*LOG(PARCOR
/YNOM) +C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)
*LOG(QARCOR(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.812209	Mean dependent var	13.54470
Adjusted R-squared	0.789308	S.D. dependent var	0.375930
S.E. of regression	0.172556	Sum squared resid	1.220805
Durbin-Watson stat	1.228922		

Equation: LOG(QOTROS) = C(21) +C(22)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR
/YNOM)*SARCOR +C(24)*LOG(POTROS/YNOM) +C(6)
*LOG(QOTROS(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.944770	Mean dependent var	12.25063
Adjusted R-squared	0.938034	S.D. dependent var	0.613384
S.E. of regression	0.152689	Sum squared resid	0.955872
Durbin-Watson stat	1.293870		

Equation: PMOND = C(31) +C(32)*IPCHOC +C(33)*IPLACT -C(14)*(1
-C(6))/(C(4)*C(14)-C(5)^2*0.164251)*PMHAT
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.991837	Mean dependent var	2150.733
Adjusted R-squared	0.990612	S.D. dependent var	1101.750
S.E. of regression	106.7498	Sum squared resid	455820.7
Durbin-Watson stat	0.615914		

Equation: PARCOR = C(41) +C(32)*IPCHOC +C(33)*IPLACT -C(4)*(1
-C(6))/(C(4)*C(14)-C(5)^2*0.164251)*PAHAT
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.994660	Mean dependent var	1737.188
Adjusted R-squared	0.993859	S.D. dependent var	904.6201
S.E. of regression	70.89117	Sum squared resid	201022.3
Durbin-Watson stat	0.667456		

System: BERTRANDVSCOURNOT
Estimation Method: Three-Stage Least Squares
Date: 05/15/24   Time: 19:52
Sample: 2 48
Included observations: 47
Total system (balanced) observations 235
Iterate coefficients after one-step weighting matrix
Convergence achieved after: 1 weight matrix, 10 total coef iterations

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.142102	0.639410	4.914063	0.0000
C(2)	0.001677	0.002314	0.724965	0.4693
C(3)	0.286855	0.041053	6.987403	0.0000
C(4)	-0.999173	0.125854	-7.939131	0.0000
C(5)	0.276389	0.088850	3.110746	0.0021
C(6)	0.527165	0.052054	10.12718	0.0000
C(11)	1.988276	0.921030	2.158752	0.0320
C(12)	0.000768	0.002009	0.382182	0.7027
C(14)	-1.296611	0.222434	-5.829183	0.0000
C(21)	2.610824	0.816973	3.195726	0.0016
C(22)	0.001288	0.002760	0.466589	0.6413
C(24)	-1.062009	0.241485	-4.397832	0.0000
C(31)	-100.4067	33.43527	-3.003018	0.0030
C(32)	0.839354	0.274467	3.058126	0.0025
C(33)	1.047677	0.269222	3.891502	0.0001
C(36)	-41.61307	29.94673	-1.389570	0.1661
C(41)	-128.9149	27.45235	-4.695953	0.0000

Determinant residual covariance 13.80829

Equation: LOG(QMOND) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PMOND/YNOM) +C(5)*LOG(PARCOR/YNOM)*SARCOR
+C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)*LOG(QMOND(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.766695	Mean dependent var	12.73075
Adjusted R-squared	0.738243	S.D. dependent var	0.422652
S.E. of regression	0.216238	Sum squared resid	1.917113
Durbin-Watson stat	0.825301		

Equation: LOG(QARCOR) = C(11) +C(12)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(14)*LOG(PARCOR
/YNOM) +C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)
*LOG(QARCOR(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.829378	Mean dependent var	13.54470
Adjusted R-squared	0.808571	S.D. dependent var	0.375930
S.E. of regression	0.164479	Sum squared resid	1.109191
Durbin-Watson stat	1.220125		

Equation: LOG(QOTROS) = C(21) +C(22)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR
/YNOM)*SARCOR +C(24)*LOG(POTROS/YNOM) +C(6)
*LOG(QOTROS(-1))

Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C

Observations: 47

R-squared	0.943893	Mean dependent var	12.25063
Adjusted R-squared	0.937051	S.D. dependent var	0.613384
S.E. of regression	0.153896	Sum squared resid	0.971043
Durbin-Watson stat	1.258942		

Equation: PMOND = C(31) +C(32)*IPCHOC +C(33)*IPLACT -(1-C(6))
/C(4)*PMHAT +C(36)*(PMCFIT-PMBFIT)

Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C

Observations: 47

R-squared	0.991639	Mean dependent var	2150.733
Adjusted R-squared	0.990619	S.D. dependent var	1101.750
S.E. of regression	106.7099	Sum squared resid	466866.7
Durbin-Watson stat	0.595510		

Equation: PARCOR = C(41) +C(32)*IPCHOC +C(33)*IPLACT -(1-C(6))
/C(14)*PAHAT +C(36)*(PACFIT-PABFIT)

Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C

Observations: 47

R-squared	0.994924	Mean dependent var	1737.188
Adjusted R-squared	0.994305	S.D. dependent var	904.6201
S.E. of regression	68.26668	Sum squared resid	191073.9
Durbin-Watson stat	0.671157		

System: COURNOTVSBERTRAND
Estimation Method: Three-Stage Least Squares
Date: 05/15/24 Time: 19:56
Sample: 2 48
Included observations: 47
Total system (balanced) observations 235
Iterate coefficients after one-step weighting matrix
Convergence achieved after: 1 weight matrix, 10 total coef iterations

	Coefficient	Std. Error	t-Statistic	Prob.
C(1)	3.129531	0.634395	4.933096	0.0000
C(2)	0.001681	0.002314	0.726444	0.4683
C(3)	0.286787	0.041044	6.987301	0.0000
C(4)	-1.002285	0.125976	-7.956143	0.0000
C(5)	0.276339	0.088785	3.112436	0.0021
C(6)	0.527292	0.052024	10.13560	0.0000
C(11)	1.988446	0.920965	2.159089	0.0319
C(12)	0.000771	0.002010	0.383341	0.7018
C(14)	-1.296061	0.222429	-5.826861	0.0000
C(21)	2.609844	0.816645	3.195813	0.0016
C(22)	0.001289	0.002760	0.466892	0.6410
C(24)	-1.061812	0.241461	-4.397444	0.0000
C(31)	-100.1936	33.47906	-2.992725	0.0031
C(32)	0.830612	0.276279	3.006426	0.0030
C(33)	1.046493	0.269369	3.884986	0.0001
C(36)	40.48812	30.28997	1.336684	0.1827
C(41)	-128.5162	27.51350	-4.671022	0.0000
Determinant residual covariance		13.79874		

Equation: LOG(QMOND) = C(1) +C(2)*TREND +C(3)*WINTER +C(4)
*LOG(PMOND/YNOM) +C(5)*LOG(PARCOR/YNOM)*SARCOR
+C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)*LOG(QMOND(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.766593	Mean dependent var	12.73075
Adjusted R-squared	0.738129	S.D. dependent var	0.422652
S.E. of regression	0.216285	Sum squared resid	1.917946
Durbin-Watson stat	0.824888		

Equation: LOG(QARCOR) = C(11) +C(12)*TREND +C(3)*WINTER
+C(5)*LOG(PMOND/YNOM)*SMOND +C(14)*LOG(PARCOR
/YNOM) +C(5)*LOG(POTROS/YNOM)*SOTROS +C(6)
*LOG(QARCOR(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1))
LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.829380	Mean dependent var	13.54470
Adjusted R-squared	0.808573	S.D. dependent var	0.375930
S.E. of regression	0.164479	Sum squared resid	1.109181
Durbin-Watson stat	1.220082		

Equation: LOG(QOTROS) = C(21) +C(22)*TREND +C(3)*WINTER +C(5)*LOG(PMOND/YNOM)*SMOND +C(5)*LOG(PARCOR /YNOM)*SARCOR +C(24)*LOG(POTROS/YNOM) +C(6) *LOG(QOTROS(-1))
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1)) LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.943896	Mean dependent var	12.25063
Adjusted R-squared	0.937054	S.D. dependent var	0.613384
S.E. of regression	0.153893	Sum squared resid	0.971002
Durbin-Watson stat	1.258944		

Equation: PMOND = C(31) +C(32)*IPCHOC +C(33)*IPLACT -C(14)*(1 -C(6))/(C(4)*C(14)-C(5)^2*0.164251)*PMHAT +C(36)*(PMBFIT -PMCFIT)
Instruments: TREND WINTER LOG(YNOM) LOG(QMOND(-1)) LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.991637	Mean dependent var	2150.733
Adjusted R-squared	0.990136	S.D. dependent var	1101.750
S.E. of regression	109.4227	Sum squared resid	466959.7
Durbin-Watson stat	0.595323		

Equation: PARCOR = C(41) +C(32)*IPCHOC +C(33)*IPLACT -C(4)*(1 -C(6))/(C(4)*C(14)-C(5)^2*0.164251)*PAHAT +C(36)*(PABFIT -PACFIT)
Instruments: TREND INVIERNO LOG(YNOM) LOG(QMOND(-1)) LOG(QARCOR(-1)) LOG(QOTROS(-1)) IPCHOC IPLACT C
Observations: 47

R-squared	0.994927	Mean dependent var	1737.188
Adjusted R-squared	0.994016	S.D. dependent var	904.6201
S.E. of regression	69.97538	Sum squared resid	190965.6
Durbin-Watson stat	0.670851		