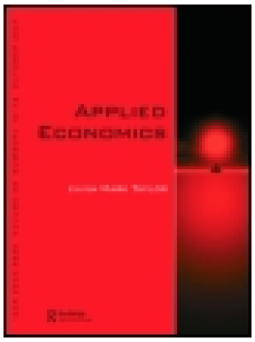

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Tacit collusion with imperfect monitoring in the Canadian manufacturing industry: an empirical study

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ABSTRACT
This article undertakes a cross-sectoral analysis of a salient empirical implication of the model of tacit collusion advanced by Abreu, Pearce, and Stachetti (1986). Specifically, we assess the prevalence of a first-order Markovian process for alternating between price wars and collusive periods through nonparametric tests. The analysis focuses on 30 different industries in Canada. The evidence provides weak support for optimal collusion in one industry, which is consistent with the idea that such kind of collusive arrangements is unusual, or, if collusion is all too common, that price wars as deviations from collusion are rare.

KEYWORDS
Tacit collusion; imperfect monitoring; manufacturing industry; Canada

JEL CLASSIFICATION
L13; L60

I. Introduction

Tacit collusion is an elusive phenomenon and game-theoretical models provide foundations for the presence of multiple pricing regimes (see for reviews Jacquemin and Slade 1992 and Rees 1993a). Furthermore, influential models by Green and Porter (1984) and Rotemberg and Saloner (1986) justify price wars as an equilibrium phenomenon for sustaining collusion, which contrasts with Friedman (1971), who postulates an infinite Nash-reversal in the punishment phase of an infinitely repeated trigger strategy oligopoly game. The nature of price wars in this context depends on the choice of punishment, the characteristics of shocks and the prevalent information structure (see Slade 1990; Lu and Wright 2010; Knittel and Lepore 2010).

The main goal of this article is to provide further empirical evidence about a specific class of game-theoretical models with embedded price wars. Noting the scarcity of empirical evidence of price wars, we extend the empirical literature by undertaking a cross-sectoral analysis, instead of the typical single market examples found in the literature. Furthermore, our analysis adopts a nonparametric test first developed by Berry and Briggs (1988) to address the possibility of an optimal collusive agreement following Abreu, Pearce and Stachetti (APS; 1986) and Knittel and Lepore (2010).

For our application, we consider a test of the Markovian implication of the APS model in the case of homogeneous and more narrowly defined industries within Canada's manufacturing industry. Such an application based on monthly data is appealing, as we conceive criteria for defining price wars that reflect not just the price variation in the product but also price changes related to (weighted) input components. The rationale is that cost asymmetries may affect collusion (as in Ivaldi et al. 2003). Unlike prior studies, we investigate the consistency with game-theoretical models outside the realm of an explicit cartel. Yet we expect an optimal collusive equilibrium to be relatively rare, even if we are expansive in our definition of price wars.

Our article hinges on empirical markers for detecting collusive conduct that are suggested by specific empirical implications accruing from the APS model. However, as we shall mention later, there are other empirical screen criteria for collusion based on different patterns for the variance of prices as considered by Abrantes-Metz et al. (2006) and Bolotova, Connor, and Miller (2008) that reflect observable implications of different theoretical models.

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In our application, the results indicate the possibility of tacit collusion in only one industry, plastic bottles, consistent with our expectations that such regimes are rare. Robustness checks show that if we consider simply price changes, with no variation of input prices, we cannot reject the existence of tacit collusion in most industries, which we would expect, as prices by itself, are noisy. The article is organized as follows. Section II discusses conceptual background aspects related to the APS model and empirical criteria for delineating price wars. Section III presents the basic aspects of the BB test. Section IV discusses data sources and presents the empirical results of the tests. Section V brings some final comments.

II. Tacit collusion and price wars

Basic conceptual aspects

The Abreu, Pearce, and Stacchetti (1986) model extends an influential text by Green and Porter (1984). A well-known signal extraction problem emerges from independent and identically distributed demand shocks that make deviations from collusion difficult to detect. Beyond the standard concavity assumption about the objective function of firms, an important assumption of the model is the monotone likelihood ratio property that indicates that the price distribution conditional on the aggregate output Q_t is such that a smaller price is more likely to be associated with a larger quantity Q_t than a small one (e.g. see Tirole 1988; Hajivassiliou 1989). The hypothesis is important because it allows for less restrictive behaviours than those prevalent in the Green and Porter model.

The APS model legitimates price wars as an equilibrium phenomenon. In collusive periods, firms produce q^+ and obtain a payoff of V^+ that refers to the best element in the set of perfect symmetric equilibria. However, if one firm observes a price below the trigger p^+, a punishment phase is initiated in such a way that firms operate with q^-, which corresponds to larger output, and leads to a smaller payoff given by V^-. This case refers to the worst element at the set of perfect symmetric equilibria.

Whether an industry remains in the punishment phase or resumes a cooperative phase depends on a second trigger p^-. If $p > p^-$, the industry remains in the punishment phase, whereas collusion resumes if $p < p^-$.

An important implication of the dynamic model of APS is that upon obtaining an indicator variable for prevalence of price wars one can justify a first-order Markov process and thus the probability that a state of high profits that prevails in period t depends only on the state at period t_{-1}. An empirical test on the Markovian hypothesis of the APS model, using on a nonparametric approach, is found in Berry and Briggs (1988) and encounters further applications in Briggs (1996) and Zeidan and Resende (2010). In the case of tacit collusion, it is then crucial to discuss criteria for empirically defining price wars.

A distinct observable implication of collusive models of oligopoly emerges from Athey, Bagwell, and Sanchirico (2004) and Harrington and Chen (2006) that consider a dynamic Bertrand setting with private i.i.d. cost information over time and across firms. Those models emphasize the exchange of cost information across firms as a facilitating device for collusion, but recognize challenges pertaining to the incentives for revealing information by firms with different levels of efficiency.[1] A salient implication that emerges from both models is the prevalence of a lower price variance in the collusive regime that can reflect how costly it is to induce cost revelation by firms or yet indicate the goal of minimizing the probability of detection of cost pass-through (see Abrantes-Metz et al. 2006 for a related discussion). Altogether, the aforementioned theoretical models legitimate empirical screen tests for collusion based on the standard high mean for prices and also on lower variances as we shall further comment in the next section.

Empirical delineation of price wars

The first wave of the empirical literature dealing with models of price wars includes Porter (1983), Lee and Porter (1984) and Ellison (1994). All sought to detect consistencies with game-theoretical collusive models by studying the well-known Joint

[1]The role of information exchange in oligopoly is empirically investigated by Clark and Houde (2014) in the context of a Canadian gasoline market. In particular, they analyse the effect of explicit communication across firms on the adjustment ratio for prices. Evidence indicates that price changes are asymmetric, while cost changes are not. That would contrast with a constant mark-up rule often associated with collusive pricing.

Executive Committee cartel. Later developments concentrated on other cases, with different methodologies used to derive price war periods, which are usually analysed by observing the market clearing prices over a period of time, subject to additional conditions. The main challenge in precisely defining the beginning and end of a price war in the present context is determining the extent to which a price decrease results because of an undercutting of prices by firms with the sole intention of punishing deviation from a collusive period or other multiple causes that may result in a price decrease. For example, fluctuations in demand, changes in productive capacity, costs shocks and firms' strategic behaviour other than punishment for a collusive agreement can also cause a sharp price decrease. The theoretical model of Abreu, Pearce, and Stacchetti (1986) on which we base our empirical analysis includes informational noise, and any one of these reasons can spark the probability of phase transitions initiating a price war, so it is difficult to translate the necessary indicator of a price war in the model to real data.

The precise definition of a price war, in terms of duration and characteristics, also depends on the idiosyncrasies of particular industries and the quality of data available. Morrison and Winston (1990) define price wars in the aviation market as a situation in which prices fall more than 20% in a single quarter. The war ends when prices increase, no matter by how many percentage points. Zhang and Round (2011) use the same start criterion, but they define the end of a price war as a situation in which prices go up by 5%. Busse (2002) uses a qualitative criterion, appealing to periodical articles and other reports that indicate the existence of a price war. Borenstein and Shepard (1996) analyse accounting data, arguing that a pointer of prices war is disclosed by the price of the companies' shares. Once one defines price war criteria, there is still the need to determine the modelling strategy to screen for collusion.

Variance screen for collusion

The APS model leads to a Markovian pattern for the indicator variable referring to prices wars, which form the basis of our screening test for collusion. The literature on empirical markers for collusive conduct supports empirical screening devices to aid policymakers. A distinct, but complementary approach to APS, explores the observable implication of lower price variance in collusive phases that would be coupled with usual expected higher mean for prices in such phases. Abrantes-Metz et al. (2006) explore such patterns, while in Abrantes-Metz et al. (2012) prices cluster together in nonrandom patterns. Bolotova, Connor, and Miller (2008) consider ARCH and GARCH to assess the conditional variance. All these models allow researchers to simultaneously investigate the behaviour of the first two moments of the price distribution during collusion by focusing on the coefficient for a related dummy variable.

More recently, Blanckenburg, Geist, and Kholodilin (2012) expand variance screening by looking beyond mean and variance at the third (skewness) and fourth (kurtosis) unconditional moments of price distributions. The authors contend that higher order moments of the price distribution should be investigated because mean and price variation could be influenced by price trends. It is worth mentioning that even in the case of well-recognized collusive activity the previous applications of the variance screen procedures led the authors to make relatively cautionary remarks as collusion detection was not as successful as it would be desired. What are the conditions for screening tests in the previous literature? The first is that possible collusive periods are known, while the second is that high-frequency price dispersion reveals collusive agreement. In the present article, we consider an approach that can provide an initial screening of potential collusive behaviour by a proactive policymaker. Because it is a conservative approach, it is unlikely to yield false positives, even though possible collusion in some markets will not be detected by our method. In any case, one must reckon that the temporal aggregation of monthly data can mask important variability in the data and that ideally one should seek weekly data and in some contexts even daily data. Thus, our approach provides a conservative assessment of collusion.

Take the argument of Doane et al. (2015) that screening for collusion fails for one of three reasons: (i) the empirical indicator cannot distinguish between a competitive null hypothesis and a collusive alternative; (ii) that the null is not indicative of competition, and the alternative indicative of collusion; or (iii) the world does not follow either the competitive or collusive hypotheses. Here we want to make sure that our approach can only fail because of (i), but never (ii). Hence, our careful empirical strategy following APS and a parsimonious specification following monthly prices in narrowly defined industries.

Our sectoral approach uses data on industry costs and market prices, but we cannot observe margins directly, which means we cannot use approaches such as Borenstein and Shepard (1996) because they rely on firm-level data.[2] We also use monthly data, and cannot follow Abrantes-Metz et al. (2006, 2012) and Bolotova, Connor, and Miller (2008). We do have some qualitative indicators, especially newspaper articles that show periods of price war in some industries in Canada during the period analysed. However, we rely on quantitative data rather than the qualitative approach of Busse (2002). This way, we use a modified version of the Morrison and Winston (1990) approach, with the recognition that a methodology based solely on the analysis of prices and costs variations can present the problem of specification and diagnosis errors, but is an improvement on a pure price criterion. In particular, we consider observations on net price changes with respect to SD benchmarks to indicate a regime shift – more details are provided in the section 'Data construction'.

We try to unearth collusive and competitive periods from the data through a conservative approach that is useful to identify collusive behaviour of the type described by APS – waves of collusion, price wars, collusive *ad infinitum*. We argue that our approach should be used as a first screening by a proactive regulator as a timely way to identify the possibility of collusive arrangements, with the caveat that the parsimonious application will most likely miss collusive behaviour that would not follow APS or cannot be captured by our criterion of price wars and the testing procedure based on Berry and Briggs (1988) and Briggs (1996).

III. The Berry and Briggs test

Berry and Briggs (1988) and Briggs (1996) focus on an empirical implication of the APS model related to the prevalence of a Markov process for an indicator variable to classify a period as collusive or subject to a price war. The starting point for the nonparametric test considers a binary series $\{It\}_{t=0}^{T}$ that represents a collusive state in period t if $I_t = 1$ and a price war if $I_t = 0$. The null hypothesis of the test is a Markov process of order K, tested against an alternative hypothesis of a Markov process of order $M > K$. A useful summary of the test procedure appears in Briggs (1996) and Zeidan and Resende (2010), and the current presentation benefits from the latter, since it provides additional details for the estimation of the parameters. First, we divide the series into terms of two sets S_i^M, with $i = 0{,}1$, to construct a binary indicator variable I_t . For our application, we consider the case of a null hypothesis of a first-order Markov process ($K = 1$) versus an alternative hypothesis of a second-order process ($M = 2$). Second, we partition the series in $2^M = 4$ possible histories at (t_{-1}, t_{-2}) as given by (0,0), (0,1), (1,0) and (1,1). A first-order Markov process implies that the state of the indicator variable in period t depends only on the prevailing state at t_{-1}, but not t_{-2}. Therefore, information available at t_{-2} should not be relevant and conditional to all histories H_i^M and H_j^M that include the same period histories for K periods, one should have $P(I_t = 1/H_i^M) = P(I_t = 1/H_j^M)$ under the null hypothesis.

The indicator variable $I_t \in S_0^M$ can be conceived in terms of independent essays conditional on a given history. Thus, a binomial distribution can be justified with a Bernoulli distribution in each period and a consistent estimator can be based on the method of moments. Let $\mu i = \sum It\, C\, S_i^M It/Ni$ denote the proportion of situations in which $I_t = 1$ given $I_t \in S_i^M$ and N_i is the number of observations in S_i^M. It follows that we consider four sub-samples for this test in the case of a first-order Markov set-up. The sample mean provides a consistent estimator of the population mean $\mu°$. Similarly, $vi = \mu i(1 - \mu\ i)$ is a consistent estimator of the

[2]However, the approach advanced by Borenstein and Shepard (1996) is distinct from the aforementioned variance screen procedures. Essentially it focuses on the sign of the coefficient of the variable proxying expected demand on margins, and the idea is to check for consistency with a prediction suggested by Rotemberg and Saloner (1986).

population variance $\nu°$, where $\sqrt{N_i}[(\mu i - \mu_i^0)/\sqrt{\nu i}$ converges to a standard normal distribution. With a first-order Markov process, we need to impose restrictions to ensure that the means are equal for the M-histories that contain the same k-history, where $\boldsymbol{R}$ is a matrix with dimension $2^K(2^{M-K}-1) \times 2^M$. Therefore, we should consider $\boldsymbol{R}\mu° = 0$, where $\mu°$ denotes the vector of means. Under the null hypothesis, $\boldsymbol{R}\mu$ is normally distributed with mean 0 and variance $\boldsymbol{RVR}^T$, where $\boldsymbol{V}$ = diag $\{\nu_1/N_1, \ldots \nu_4/N_4\}$ stands for the variance matrix for μ and $W \equiv (\boldsymbol{R}\mu)^T(\boldsymbol{RVR}')^{-1}(\boldsymbol{R}\mu)$ follows a χ^2 distribution with the parameter given by the number of restrictions. In our application, we have $K = 1$ and $M = 2$ and so the restriction matrix contains two rows, given respectively by [1–1 0 0] and [0 0 1–1]. In fact, they impose the restriction that for a common history at t_{-1} we should have equal means independent of the history at t_{-2}, such that $\mu_1 = \mu_2$ and $\mu_3 = \mu_4$. The test statistic follows a χ^2 under the null hypothesis of a first-order Markov process, rather than a second-order alternative.

IV. Empirical analysis and results

Data construction

We use monthly data for the manufacturing industry in Canada, available from Canada's national statistical agency (http://www.statcan.gc.ca). Sectoral data are available at the five- and six-digit level of the North American Classification System (NAICS) for 2002. We considered changes in net prices to devise the criteria for defining price wars. Specifically, as a proxy for net price changes we considered the following expression:

$$\Delta NP_i = \Delta P_i - \sum_{j=1}^{J} w_{ij} \Delta IP_j \qquad (1)$$

where ΔP_{iy} = (ln P_{it} – ln $P_{i,t-1}$) * 100, and ΔIP_{it} = (ln IP_{it} – ln $IP_{i,t-1}$) * 100. We therefore consider changes in prices of the product net of weighted changes in the main input prices. Data from CANSIM Statistics Canada reflect information contained in 60 of the 3206 tables in that database.[3] The adopted criterion for inputs considers the J items that constitute at least 80% of the costs.[4] The weight refers to the average cost share because the cost shares show little variation during the study period. The sample for this study referred to monthly data over the 1992–1/2009–3 period.

The data set from *Statistics Canada* provide a unique opportunity for properly incorporating the weighted effects of input prices in order to conceive a net change in the price of a given product. In fact, criteria for price wars that are based solely on the output price could indicate trajectories that reflect costs pass-through accruing from the ability to exercise market power. In contrast, the article aims at capturing (tacitly) coordinated behaviour between firms that can extrapolate reactions to cost shocks. In that sense, the testing of the Markovian implications of the APS model emerges as a relatively simple and informative approach. Interestingly, previous applications mostly focused on explicit cartels like the well-known Joint Executive Committee, in which the actual occurrence of price wars was clearly reported. The consideration of the referred approach in terms of a large-scale investigation without clear-cut *a priori* information on price wars is timely and could provide an interesting exclusion test for market regulators.

Furthermore, it is important to exercise additional care in selecting the industrial sectors in the present study. The Abreu, Pearce, and Stacchetti (1986) model refers to homogeneous products, so we need to select homogenous and narrowly defined industries, which prompted the initial selection of 30 highly disaggregated industries. However, limited data availability on cost components in some sectors restricted our potential sample. We consider a parsimonious criterion for identifying price wars. We assume that a price war starts if a reduction in net prices of at least 2 SDs has taken place in the current period relatively to period t_{-1}, whereas we postulate that the collusive phase has been resumed if we observe an increase of 1 SD. Other authors use purely a price criterion to determine the different

[3]Examples include Table 281–0035 – average hourly earnings for salaried employees (paid a fixed salary) (SEPH), including overtime, unadjusted for seasonal variation, for selected industries classified using the North American Industry Classification System (NAICS), monthly; Table 329–0044 – industry price indexes for primary metal products and metal fabricating products, monthly (index, 1997 = 100), and Table 329–0046 – industry price indexes for electrical and communication products, nonmetallic mineral products, petroleum and coal products, monthly (index, 1997 = 100).

[4]Table 329–0073, for instance, shows electric power prices for industrial purposes.

phases of a price war, as previously mentioned. This is the right path if one has prior information on the existence of a price war in a particular industry. Here we are searching for collusive behaviour without prior knowledge of possible price wars in the selected homogeneous industries. The main characteristic of a price war is not only a decrease in prices, but a decrease in profits. Here we approximate profits by observing variations on price margin (price minus variable costs). We consider the start of a price war by a 2 SD change in the price margin, approximated by the difference in variation of prices minus inputs. Looking at price alone is not ideal in our scenario, because of the possibility of noise in the data, related to supply shocks. We try to improve on the regular criterion used in the literature by considering price margin variation as a source of identifying price wars.

The criterion would be even more appealing in the case of normality, though the assumption of normality for net price changes is untenable in 26 of the 30 sectors, as indicated by the Shapiro–Wilk test.

The summary statistics and Shapiro–Wilk tests are reported in Table 1.

The optimal collusion equilibria are likely to be a rare phenomenon, and we are proposing a simple criterion for defining a price war that will generate the indicator variable we use to test for the Markovian implication of the APS model. Ideally, we would prefer weekly data as the available monthly data can masquerade part of the price variation. Thus, there is no obvious reason to expect the widespread prevalence of collusive arrangement along the lines of APS in several industries, and the eventual rare occurrence of those mechanisms does not mean that the model is not properly tracking price changes. The APS model deals with implications on price war patterns and does not aim to directly explain price changes.

Our conservative approach for defining price wars provides more confidence in the results that emerge from the tests.

Empirical results

The results of the tests for the selected industries are presented in Table 2.

The evidence, using a 5% significance level, does not allow the nonrejection of the hypothesis of a first-order Markov for all industries. However,

Table 1. Summary statistics net price changes (including weighted changes for price inputs).

Sector	Mean	SD	Min	Max	*W*	*p*-Value
Flour milling (31121)	−0.0001	0.0163	−0.0539	0.0570	0.9726	0.0005
Vegetable fat and oil (31122)	0.0006	0.0235	−0.0758	0.0763	0.9934	0.4899
Sugar manufacturing (31131)	0.0026	0.0172	−0.0462	0.0698	0.9713	0.0003
Pulp mills (32211)	0.0008	0.0324	−0.1440	0.0857	0.9545	0.0000
Paper mills (322121)	0.0006	0.0180	−0.0412	0.0944	0.9540	0.0000
Newsprint mills (322122)	0.0007	0.0219	−0.0579	0.1087	0.9637	0.0000
Paperboard mills (32213)	0.0009	0.0181	−0.0612	0.0798	0.9095	0.0000
Paperboard container (32221)	0.0007	0.0120	−0.0405	0.0374	0.9724	0.0004
Paper bag and coated (32222)	0.0001	0.0108	−0.0433	0.0423	0.9694	0.0002
Synthetic dye (32513)	−0.0014	0.0231	−0.0604	0.0981	0.9785	0.0030
Resin, synthetic rubber (32521)	−0.0009	0.0136	−0.0415	0.0522	0.9832	0.0145
Fertilizer manufacturing (32531)	0.0041	0.0300	−0.1424	0.1104	0.9242	0.0000
Pesticide and other agr (32532)	−0.0014	0.0159	−0.0566	0.0504	0.9660	0.0001
Plastic pipe, pipe fitting (32612)	0.0003	0.0139	−0.0444	0.0631	0.9805	0.0057
Laminated plastic plate (32613)	0.0003	0.0103	−0.0358	0.0321	0.9846	0.0236
Polystyrene, urethane (32614)	0.0003	0.0113	−0.0573	0.0339	0.9571	0.0000
Plastic bottle (32616)	0.0000	0.0099	−0.0285	0.0307	0.9936	0.5153
Veneer plywood (321211)	0.0001	0.0328	−0.1376	0.1389	0.9511	0.0000
Wood window (321911)	−0.0007	0.0142	−0.0378	0.0456	0.9914	0.2625
Wood container (32192)	0.0007	0.0150	−0.0494	0.0397	0.9909	0.2216
Glass product manufacturing (32721)	−0.0007	0.0183	−0.0844	0.0697	0.9086	0.0000
Cement manufacturing (32731)	0.0003	0.0153	−0.0694	0.0592	0.8934	0.0000
Ready-mix concrete (32732)	−0.0001	0.0154	−0.0702	0.0473	0.9139	0.0000
Concrete product (32733)	−0.0004	0.0162	−0.0693	0.0493	0.9359	0.0000
Lime manufacturing (32741)	0.0014	0.0176	−0.0794	0.0605	0.9100	0.0000
Aluminium production (33131)	−0.0019	0.0460	−0.1364	0.1651	0.9808	0.0063
Metal tank (33242)	0.0007	0.0149	−0.0491	0.0615	0.9475	0.0000
Power, distribution manufacturing (335311)	0.0014	0.0194	−0.0561	0.0814	0.9464	0.0000
Battery manufacturing (33591)	0.0000	0.0123	−0.0654	0.0716	0.8935	0.0000
Communication and energy wire (33592)	0.0000	0.0148	−0.0626	0.0606	0.9383	0.0000

Note: The sectors are listed with their NAICS classification codes in parentheses.

Table 2. Nonparametric tests for First-order Markov process for the indicator variable.

	History (t−1,t−2)													
	(1,1)			(1,0)			(0,1)			(0,0)				
Sector	μ	Var	N	μ	Var	N	μ	Var	N	μ	Var	N	Test statistic	p-Value
Flour milling (31121)	0.964	0.035	165	0.166	0.138	6	1	0	6	0.179	0.147	28	155.990	0.000
Vegetable fat and oil (31122)	0.984	0.016	188	0	0	4	0.667	0.222	3	0.4	0.24	10	16.0208	0.000
Sugar manufacturing (31131)	0.976	0.023	167	0	0	4	1	0	4	0.133	0.116	30	7.00E+03	0.000
Pulp mills (32211)	0.981	0.019	159	0	0	3	1	0	3	0.075	0.069	40	8.76E+03	0.000
Paper mills (322121)	0.976	0.024	166	0	0	4	1	0	4	0.129	0.112	31	6.93E+03	0.000
Newsprint mills (322122)	0.976	0.024	166	0	0	4	1	0	4	0.129	0.112	31	6.93E+03	0.000
Paperboard mills (32213)	0.989	0.011	174	0	0	2	1	0	2	0.074	0.069	27	1.53E+04	0.000
Paperboard container (32221)	0.99	0.01	193	0	0	2	1	0	1	0.111	0.099	9	1.85E+04	0.000
Paper bag and coated (32222)	0.964	0.035	167	0.5	0.5	6	1	0	6	0.115	0.102	26	201.9113	0.000
Synthetic dye (32513)	0.976	0.023	169	0.2	0.4	5	0.8	0.16	5	0.154	0.13	26	18.803	0.000
Resin, synthetic rubber (32521)	0.965	0.034	142	0	0	5	1	0	5	0.094	0.085	53	4.40E+03	0.000
Fertilizer manufact (32531)	0.969	0.03	161	0.4	0.489	5	1	0	5	0.088	0.08	34	354.631	0.000
Pesticide and other agr (32532)	0.972	0.027	179	0	0	5	1	0	5	0.313	0.215	16	6.26E+03	0.000
Plastic pipe,pipe fitting (32612)	0.977	0.023	172	0.25	0.433	4	1	0	4	0.12	0.106	25	188.206	0.000
Laminated plastic plate (32613)	0.973	0.027	183	0.5	0.5	4	1	0	4	0.143	0.122	14	85.785	0.000
Polystyrene, urethane (32614)	0.968	0.031	190	0.6	0.489	5	1	0	5	0.4	0.24	5	8.883	0.003
Plastic bottle (32616)	0.985	0.015	199	0.5	0.5	2	1	0	2	0.5	0.25	2	2.940	0.086
Veneer plywood (321211)	0.985	0.015	196	0	0	3	1	0	3	1	0	3	n.a.	n.a.
Wood window (321911)	0.964	0.034	168	0.428	0.495	7	0.857	0.122	7	0.174	0.144	23	23.712	0.000
Wood container (32192)	0.973	0.025	184	0.4	0.490	5	1	0	5	0.273	0.198	11	32.677	0.000
Glass product manuf (32721)	0.953	0.045	149	0.333	0.471	9	0.777	0.172	9	0.158	0.133	38	24.215	0.000
Cement manufacturing (32731)	0.955	0.043	178	0.5	0.5	8	1	0	8	0.364	0.231	11	22.550	0.000
Ready-mix concrete (32732)	0.967	0.032	183	0.571	0.494	7	0.857	0.122	7	0.375	0.234	8	7.179	0.007
Concrete product (32733)	0.96	0.038	176	0.571	0.494	7	1	0	7	0.2	0.16	15	62.132	0.000
Lime manufacturing (32741)	0.972	0.028	176	0.428	0.494	7	0.714	0.204	7	0.267	0.196	15	8.9106	0.003
Aluminium production (33131)	0.978	0.021	182	0	0	4	1	0	3	0.25	0.188	16	8.15E+03	0.000
Metal tank (33242)	0.963	0.035	164	0.428	0.494	7	0.857	0.122	7	0.148	0.126	27	26.7109	0.000
Power, distribution manuf. (335311)	0.978	0.021	186	0	0	3	1	0	3	0.231	0.178	13	8.51E+03	0.000
Battery manufacturing (33591)	0.985	0.015	194	0	0	2	1	0	2	0.286	0.204	7	1.24E+04	0.000
Communication and energy wire (33592)	0.973	0.027	182	0.25	0.433	4	1	0	4	0.2	0.16	15	64.816	0.000

Note: The sectors are listed with their NAICS classification codes in parentheses; n.a. indicates that the test was not feasible.

marginal evidence consistent with a first-order Markov process emerges in the case of plastic bottles (p-value of 0.086).

Finally, it is worth mentioning that we consider a robustness check by focusing on gross instead of net price changes. The summary statistics and normality tests are presented in Table A1 (in the Appendix) and the latter is tenable only in one sector. The summaries for four possible sub-samples and the test statistics for the Markovian hypothesis are reported in Table A2 (in the Appendix). We contend that price wars should be defined with a preferential criterion that encompasses the role of input prices as in the initial analysis reported in Table 2. The results for the simpler criterion that ignores the trajectories of input prices are very different and for conceptual reasons less appealing. In that case, collusion appears to be a relatively common phenomenon what highlights the necessity of exercising careful attention in the definition of price wars. We argue that simple price criteria may be misleading in the identification of price wars, unless one has previous information on the industries' behaviour. Here we propose large-scale analysis with no predefined information on the industries. Hence, gross price fluctuations would not reveal the underlying strategies by companies, given that in homogeneous markets price fluctuations are common.

V. Final comments

The study aims to provide a large-scale sectoral investigation of the Markovian implications for a price war indicator using the tacit collusion model by Abreu, Pearce, and Stacchetti (1986). Detailed monthly data about the Canadian manufacturing industry enable us to undertake this analysis for disaggregated and narrowly defined industries. Moreover, the availability of input cost information is instrumental for defining and implementing a price war criterion which provides the basis for the test, and is an improvement over a pure price criterion.

The evidence ultimately indicates marginal support for the Markovian hypothesis, but only in the case of the plastic bottles industry. Evidence of optimal collusion offers an important tool for market regulators. In the absence of explicit collusion, or a so-called ‘smoking gun’, indirect inferences are worth being considered, as long as a parsimonious approach is used to avoid wrong inferences about collusive behaviour (Doane et al. 2015).

Nevertheless, more detailed data are clearly required for optimal analysis of potential collusive behaviour. This would include details about the informational structure that prevails in different industries, and yet more specific firm-level information. In fact, the New Empirical Industrial Organization literature has made important progress in the empirical identification of market power, but data requirements are demanding for competition agencies. Even at a more aggregate level, data for prices, quantities and demand and cost shifters might not be readily available (see Bresnahan 1989 for an early overview on that strand of the literature) and therefore the estimation of more structural models can be challenging from the perspective of a policymaker. Nevertheless, as suggested by Phlips (1995), game-theoretical models can be useful from a policy perspective and different empirical implications can be tested to assess collusive behaviours under less demanding data requirements. The nonparametric approach implemented in this article provides such an example. Another possibility is proposed by Osborne and Pitchik (1987) and the related empirical analysis is considered by Rees (1993b), in which collusion is tested in the context of a salt duopoly by taking as reference information on profits and production capacity. Therefore, it appears that beyond the academic interest, simple tests for collusion could expand the toolbox of policymakers in competition agencies.

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Appendix

Table A1. Summary statistics: gross price changes (excluding weighted changes for price inputs).

Sector	Mean	SD	Min	Max	*W*	*p*-Value
Flour milling (31121)	0.0014	0.0157	−0.0589	0.0798	0.9040	0.0000
Vegetable fat and oil (31122)	0.0023	0.0264	−0.0696	0.0757	0.9938	0.5418
Sugar manufacturing (31131)	0.0038	0.0231	−0.0592	0.0715	0.9801	0.0049
Pulp mills (32211)	0.0020	0.0347	−0.1607	0.1011	0.9336	0.0000
Paper mills (322121)	−0.0018	0.0185	−0.0428	0.0884	0.9509	0.0000
Newsprint mills (322122)	0.0019	0.0226	−0.0526	0.1027	0.9584	0.0000
Paperboard mills (32213)	0.0023	0.01022	−0.0303	0.0496	0.8286	0.0000
Paperboard container (32221)	0.0023	0.0102	−0.0303	0.0496	0.7817	0.0000
Paper bag and coated (32222)	0.0016	0.0064	−0.0250	0.0428	0.8364	0.0000
Synthetic dye (32513)	0.0019	0.0088	−0.0478	0.0406	0.8548	0.0000
Resin synthetic rubber (32521)	0.0016	0.0160	−0.0579	0.0508	0.9800	0.0048
Fertilizer manufacturing (32531)	0.0065	0.0311	−0.1638	0.1393	0.8318	0.0000
Pesticide and other agr (32532)	0.0010	0.0074	−0.0321	0.0569	0.5679	0.0000
Plastic pipe, pipe fitting (32612)	0.0016	0.0122	−0.0381	0.0670	0.9389	0.0000
Laminated plastic plate (32613)	0.0016	0.0048	−0.0149	0.0283	0.9435	0.0000
Polystyrene urethane (32614)	0.0016	0.0088	−0.0573	0.0342	0.8092	0.0000
Plastic bottle (32616)	0.0013	0.0074	−0.0185	0.0342	0.9450	0.0000
Veneer plywood (321211)	0.0016	0.0326	−0.1389	0.1348	0.9540	0.0000
Wood window (321911)	0.0008	0.0062	−0.0221	0.0513	0.6508	0.0000
Wood container (32192)	0.0023	0.0090	−0.0321	0.0366	0.8279	0.0000
Glass product manufacturing (32721)	0.0009	0.0088	−0.0418	0.0533	0.7472	0.0000
Cement manufacturing (32731)	0.0219	0.0076	−0.0363	0.0338	0.6975	0.0000
Ready-mix concrete (32732)	0.0018	0.0072	−0.0170	0.0448	0.7183	0.0000
Concrete product (32733)	0.0015	0.0090	−0.0568	0.0514	0.6735	0.0000
Lime manufacturing (32741)	0.0030	0.0089	−0.0316	0.0462	0.9260	0.0000
Aluminium production (33131)	0.0026	0.0415	−0.1653	0.1026	0.9769	0.0018
Metal tank (33242)	0.0025	0.0060	−0.0046	0.0523	0.5636	0.0000
Power distribution manufacturing (335311)	0.0030	0.0169	−0.4836	0.0824	0.8703	0.0000
Battery manufacturing (33591)	0.0015	0.0039	−0.0124	0.0243	0.7379	0.0000
Communication and energy wire (33592)	0.0015	0.0138	−0.0653	0.0711	0.9281	0.0000

Note: The sectors are listed with their NAICS classification codes in parentheses.

Table A2. Nonparametric tests for first-order Markov process for the indicator variable [constructed upon net price changes (excluding weighted changes for price inputs)].

	History (t–1,t–2)													
	(1,1)			(1,0)			(0,1)			(0,0)				
Sector	μ	Var	N	μ	Var	N	μ	Var	N	μ	Var	N	Test statistic	p-Value
Flour milling (31121)	0.951	2.5E-04	185	1	0	8	0.875	0.014	8	0.25	0.048	4	15.918	0.000
Vegetable fat and oil (31122)	0.956	2.28E-04	183	0.7	0.021	10	0.8	0.016	10	1	0	2	5.594	0.061
Sugar manufacturing (31131)	0.927	3.84E-04	177	1	0	12	0.833	0.012	12	0.5	0.0625	4	15.530	0.000
Pulp mills (32211)	0.963	1.91E-04	188	0.857	0.017	7	0.857	0.017	7	0.333	0.074	3	3.628	0.163
Paper mills (322121)	0.973	1.38E-04	188	0.5	0.031	8	0.875	0.014	8	1	0	1	8.283	0.016
Newsprint mills (322122)	0.968	1.68E-04	186	0.556	0.027	9	0.889	0.011	9	1	0	1	7.28	0.026
Paperboard mills (32213)	0.933	3.49E-04	179	0.917	0.006	12	0.917	0.006	12	0.5	0.125	2	1.361	0.506
Paperboard container (32221)	0.933	3.46E-04	180	0.917	0.006	12	0.917	0.006	12	1	0	1	1.132	0.568
Paper bag and coated (32222)	0.946	2.74E-04	186	1	0	9	0.889	0.011	9	1	0	1	11.674	0.003
Synthetic dye (32513)	0.921	4.12E-04	177	0.929	0.005	14	1	0	14	0	na	0	n.a.	n.a.
Resin, synthetic rubber (32521)	0.938	3,22E-04	179	0.909	0.008	11	0.727	0.018	11	0.75	0.047	4	0.119	0.942
Fertilizer manufact (32531)	0.938	3,22E-04	179	0.909	0.008	11	0.818	0.014	11	0.5	0.062	4	1.442	0.486
Pesticide and other agr (32532)	0.939	3,19E-04	180	0.909	0.008	11	0.727	0.018	11	1	0	3	4.238	0.120
Plastic pipe,pipe fitting (32612)	0.946	2.71E-04	187	1	0	9	1	0	9	0	na	0	n.a.	n.a.
Laminated plastic plate (32613)	0.934	3.42E-04	181	0.917	0.006	12	1	0	12	0	na	0	n.a.	n.a.
Polystyrene, urethane (32614)	0.946	2.76E-04	185	1	0	9	0.889	0.011	9	0.5	0.125	2	11.699	0.003
Plastic bottle (32616)	0.939	3.19E-04	180	0.909	0.008	11	0.727	0.018	11	1	0	3	4.238	0.120
Veneer plywood (321211)	0.946	2.79E-04	184	0.9	0.009	10	0.9	0.009	10	1	0	1	1.338	0.513
Wood window (321911)	0.940	3.05E-04	184	1	0.009	10	0.9	0.009	10	1	0	1	12.829	0.002
Wood container (32192)	0.92	4.21E-04	175	1	0	13	0.769	0.014	14	1	0	3	19.102	0.000
Glass product manufacturing (32721)	0.932	3.61E-04	176	0.786	0.012	14	0.929	0.005	14	1	0	1	2.800	0.247
Cement manufacturing (32731)	0.914	4,53E-04	174	0.933	0.004	15	0.933	0.004	15	1	0	1	1.154	0.561
Ready-mix concrete (32732)	0.927	3.76E-04	179	0.923	0.005	13	1	0	13	0	n.a.	0	n.a.	n.a.
Concrete product (32733)	0.951	2,53E-04	184	0.889	0.011	9	0.667	0.025	9	1	0	3	4.845	0.089
Lime manufacturing (32741)	0.925	3.97E-04	174	0.857	0.009	14	0.786	0.012	14	1	0	3	4.326	0.115
Aluminium production (33131)	0.957	2.21E–04	186	1	0	9	0.667	0.025	8	1	0	2	12.871	0.002
Metal tank (33242)	0.963	1.89E-04	189	0.857	0.017	7	0.857	0.017	7	0.5	0.125	2	1.528	0.466
Power, distribution manufacturing (335311)	0.914	4.53E-04	174	0.933	0.004	15	0.933	0.004	15	1	0	1	1.154	0.561
Battery manufacturing (33591)	0.932	3.61E-04	176	0.786	0.012	14	0.929	0.005	14	1	0	1	2.800	0.247
Communication and energy wire (33592)	0.957	2.19E-04	187	0.875	0.014	8	0.75	0.023	8	1	0	2	3.153	0.207

Note: The sectors are listed with their NAICS classification codes in parentheses; n.a. indicates that the test was not feasible.