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Cartels Uncovered

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Abstract

How many cartels are there? The answer is important in assessing the need for competition policy. We present a Hidden Markov Model that answers the question, taking into account that often we do not know whether a cartel exists in an industry or not. We take the model to data from a period of legal cartels - Finnish manufacturing industries 1951 - 1990. Our estimates suggest that once born, cartels are persistent; by the end of the period, almost all industries were cartellized. Our model may be extended to identify key policy parameters from data generated under different competition policy regimes.

JEL codes: : L0, L4, L40, L41, L60.

keywords: antitrust, cartel, competition, detection, Hidden Markov models, illegal, legal, policy, registry.

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"A nation built on cartels"

(Historian Markku Kuisma (2010) on Finland).

1 Introduction

Little is known of the prevalence of cartels and, consequently, the need for competition policy. A key reason for this state of affairs is that important statistics, such as the proportion of industries (markets) that have a cartel under an existing competition policy regime, or would have a cartel if there was no competition policy, are unknown.[1] These statistics are unknown primarily because of a lack of tools to deal with a peculiar feature of cartel data: Most of the time, it is not known whether an industry has a cartel or not. The available data depend on 1) the prevalence of cartels, 2) the probability that cartels get exposed and 3) the probability that the cartels' (non)existence in the time periods prior to their exposure can be established.[2] This data generation and exposure process, once linked to a theoretical (Markov) model of cartel behavior, maps into a Hidden Markov Model (HMM) that provides a tool for competition policy analysis. We take this HMM to inter-industry panel data on nationwide Finnish legal manufacturing cartels from 1951 to 1990 and estimate the number of cartels in the (from a modern viewpoint counterfactual) state of no active competition policy.

Our HMM consists of a hidden process and an observation process that reveals information on the hidden state of the industry for some periods, but not for others. These processes can be adapted to the dynamics of cartel behavior and to the institutional environment. To show how, we use a recent theoreti-

[1] The cartels we study in this paper are defined by the Competition Authority to be nation- and therefore also industry-wide, covering all (e.g. regional) markets.

[2] An important implication of this data generation and exposure process is that a naive comparison of the proportion of observed cartels to that of non-cartellized industries would yield a biased estimate of the prevalence of cartels.

cal Markov model where industries form and dissolve cartels (Harrington and Chang 2009, Chang and Harrington 2010, referred to jointly as CH henceforth).[3] In this model, cartels face an incentive compatibility constraint (ICC). If the constraint is violated, the cartel breaks down completely. If there was no cartel in the previous period, the industry gets an opportunity to form a cartel with positive probability. Success in forming the cartel is subject to the ICC not being violated. We map the key elements of this Markov model into a HMM.

Prior to the emergence of New Empirical Industrial Organization (NEIO; see Bresnahan 1989) most cartel research used inter-industry data (e.g. Frass and Greer 1977 and Hay and Kelley 1974). More recently, Symeonidis' work on cartels (see Symeonidis 2002) has made use of the inter-industry variation in policy changes to identify the treatment effect of cartellization. Bryant and Eckard (1991) use U.S. data on exposed horizontal price fixing agreements 1961-1988 and estimate the probability of detection by the Competition Authority (CA). Other examples of the inter-industry approach include Levenstein and Suslow's (in press) study of international cartels, Miller's (2009) paper on the number of exposed U.S. cartels and Brenner's (2009) analysis of European Commission's leniency program.

Examples of the NEIO strand of the literature using data on individual industries/markets are Porter (1983), Lee and Porter (1984), Ellison (1994), Pesendorfer (2000), Porter and Zona (1993, 1999), Genesove and Mullin (1998, 2001), Knittel and Stango (2003), Röller and Steen (2006) and Asker (2010). These papers demonstrate the inner workings of a cartel. As a group, they reveal a considerable amount of heterogeneity in how cartels operate, how effective they are in sustaining collusive outcomes and in the welfare losses they generate.

[3] Building on similar insights, Miller (2009) independently develops a dynamic (Markov) model of cartel formation and dissolution and studies, using aggregate data on the number of exposed U.S. cartels, whether the leniency program that the U.S. Department of Justice introduced in 1993 reduced cartellization.

Our most important precursors are Porter (1983), Lee and Porter (1984) and Ellison (1994) who all study the Joint Executive Committee, i.e., the Chicago-Atlantic seaboard railway cartel from the 1880s. Porter (1983) and Lee and Porter (1984) allow for two hidden states of the industry - collusion and price-war in their set-up - and utilize an imperfect indicator to identify the collusive state of the industry. Ellison (1994) extends their empirical work by bringing in a Markov structure for the hidden process. These authors' objective is to estimate the collusive status of the industry and the effect of collusion on the supply relation. They utilize data on demand, cost, and collusive markers. Another important precursor is Knittel and Stango (2003), who study collusion in the local U.S. credit card markets.

Unlike that of earlier work, our objective is to estimate the prevalence of cartels using data that are revealed by CA actions.[4] Methodologically, the major difference between our and the preceding work is that we introduce the HMM modeling structure. In particular, we allow explicitly for the possibility that the state of the industry is unknown (to the researcher/CA) instead of allowing for regime classification mistakes.[5] The possibility that the state of the industry is unknown means that our model can be readily applied to a cross-section (or panel) of industries or markets; something one may want to do when studying prevalence of cartels and competition policy. The higher the number of industries in the data, the more likely it is that the researcher faces the situation where she cannot with confidence assign a "cartel/no-cartel" status to some observation(s). Indeed, we would think - and this definitely holds in our

[4]The CA actions may reveal demand and cost data on the investigated industries, but nothing about the remaining industries. Collecting demand and cost data on these may be prohibitive.

[5]Given the type of data typically available, the earlier models would require the researcher to assign either the status "cartel" or "no cartel" to each observation, while allowing for mistakes in this assignment. That is, the previous models assign probability zero to the event that the observed state of an observation is "unknown". Our HMM relates to the earlier models, as it can allow both for mistakes in labeling and the possibility that the state of the industry is not known.

application - that most of the observations are assigned the status “unknown”.

We take our HMM model to panel data on 234 Finnish manufacturing industries from 1951 to 1990. Benefits of these data are the length of the observation period and the shared institutional environment. In 109 industries, there was at least one known nationwide horizontal cartel in existence some time between 1951 - 1990. For the remaining 125 industries it is unknown whether a cartel ever existed. We have obtained data on the cartels from the Registry established in 1958 after the first Finnish competition law was enacted. Similar registries existed e.g. in Austria, Germany, Switzerland, the Netherlands, all Nordic countries and Australia. Cartels were legal during our whole observation period. They ended in the Registry either through self-reporting or through the CA approaching them. We can assign some industry-year observations to be cartel (non-cartel) observations, while for the majority we stay agnostic, assigning them status “unknown”.[6] We augment these data with industrial statistics, macroeconomic and trade variables and variables describing the workings of the Finnish Cartel Registry.

We estimate the parameters of the observation process of the HMM and the process that governed the births and deaths of the cartels. The link to modern illegal cartels is that we provide an upper bound estimate of the number of cartels - after all, while legal cartels' existence is not affected by competition policy, they are subject to (many of) the same internal incentive problems that illegal cartels face. We can therefore also answer the question: How cartellized was Finnish manufacturing in the era of legal cartels? The answer is a key piece of information in the evaluation of modern competition policy.

Our empirical application produces stark results that rhyme well with anecdotal accounts and developments in the institutional and economic environment

[6] Because of the introduction of the “unknown” state, our HMM allows us to circumvent the problem of right censoring of observed cartel durations which has plagued part of the earlier literature.

of Finland. We find that the chance of forming a cartel is around 20% and increases over our sample period. In line with Ellison (1994), the probability of a cartel continuing is very high (circa 90%). Our estimate of the proportion of manufacturing industries that had a cartel is on average close to 50% over our observation period. It is increasing over time, and reaches more than 90% by the end of the period, with a sharp jump in the early 1970s. To probe the robustness of these results, we perform several robustness tests and a counterfactual analysis. Our results survive these tests. We come up with potential explanations especially for the jump in cartellization, one of which is the high degree of corporatism of the Finnish economy in the mid 1970s.[7] In the fight against inflationary pressures of that period, the government seems to have looked favorably upon firms coordinating prices. Despite this, we remain open to the possibility that some of our results are an artefact of our modeling choices. Taken at face value, our results suggest that strict competition policy is of first order importance.

The rest of the paper is organized as follows. In the next Section, we first briefly review the relevant parts of the Chang and Harrington cartel models. We then show how a HMM that matches the collusive dynamics of these models with the observed data can be specified. In the third Section, we describe the Finnish institutional environment vis-à-vis cartels after WWII and the data. Section four is devoted to the presentation of our results and a discussion of their policy implications. Section five illustrates how our HMM can be extended to allow for a modern competition policy environment. Section six concludes.

[7]The sentiment in Finland seems to have been favorable toward cartels during our observation period. For example, in the chapter "A nation built on cartels" (Kuisma 2010), the historian Markku Kuisma makes the claim that the Finnish economy was founded on cartels throughout the 20th century. See also Fellman (2008), who in her description of the Finnish economic history emphasizes the importance of state-led economic growth and corporatism. In particular, she describes how "[c]artels fitted well into the strongly co-operative model" until the late 1980s and how the views and economic culture changed soon after the end of our sample period.

2 Modeling Cartel Births and Deaths

2.1 Cartel Dynamics

We study the rate of cartellization among Finnish manufacturing industries during an era when, bar a few exceptions that we explain in greater detail in Section 3, cartels were legal.[8] While there are many dynamic models of cartel formation and dissolution in the literature that could also suit our purposes, we consider a simplified version of the Chang and Harrington model that matches the Finnish institutional environment.

CH model an industry where (identical) firms in an industry each period simultaneously decide whether or not to collude and where collusion can be detected by a CA. We abstract the deterrence activity of the CA from the model but assume, as CH do, that being in a cartel is synonymous with actually colluding (i.e., the market outcome not being competitive).[9] Period-specific profits per firm under collusion are π; firms earn $\alpha\pi$, $\alpha \in [0, 1)$ if they compete; and a deviating firm earns $\eta\pi$, $\eta > 1$. The profit measure π has a continuously differentiable c.d.f. H_{IC} and an expected value μ. Firms have an infinite horizon with a discount factor δ.

At the beginning of a period, an industry is either in a cartel or not; this is dictated by the previous period's outcome. If the industry is not in a cartel, it gets an opportunity to form a cartel with probability $\kappa \in (0, 1)$. The remaining within-period sequence of events is the same for cartels thus born, and cartels that existed in the previous period: Given the realization of π (which the firms observe prior to deciding on cartel continuation), the ICC holds and the in-

[8] This means that the Finnish CA, or its predecessors, did not attempt to close cartels. Nor was there a leniency program in place.

[9] Being or not being in a cartel is hence a dichotomous event. For example, a "price war" would be classified as a period of no cartel. In practice, the ability of cartels to raise price may vary. Such variation can be captured by allowing for between-industry variation in model parameters (e.g. α).

dustry colludes. If it does not, the cartel dies. If the cartel does not dissolve, the industry continues in state "cartel" into the next period. The structural parameters of the model are thus μ, α, η, H_{IC}, κ, and δ.

The ICC of an industry takes the form

$$(1-\delta)\pi + \delta Y \geq (1-\delta)\eta\pi + \delta W, \tag{1}$$

where Y (W) is the scaled continuation payoff from (not) being in a cartel. Both are functions of (all of) the structural parameters. The L.H.S. of the ICC has two parts. The first denotes the current profits and the second the continuation payoff earned if there is collusion. On the R.H.S., the first term are the profits from deviating. Deviation will yield the competitive continuation payoff W, which is the second R.H.S. term.

As in CH, the expected payoff to being cartellized is defined by a recursion that can be solved through a fixed point calculation.[10] Using the fixed point with collusion, Y^*, and rearranging (1) shows that the ICC can be rewritten in terms of π:

$$\pi \leq \phi^* \tag{2}$$

where $\phi^* = [\frac{\delta(1-\kappa)(Y^*-\alpha\mu)}{(\eta-1)(1-\delta(1-\kappa))}]$ on the R.H.S. is a measure of cartel stability. Cartels collapse internally if the profit shock exceeds ϕ^*. We denote the probability that this ICC is satisfied by H.

For our purposes, this modeling framework has an important feature: It results in a Markov model for the hidden collusive dynamics of an industry and generates an unobserved sequence of cartel and non-cartel periods.

[10] Harrington and Chang (2009) set out the conditions under which cartels may be born when there is no leniency, whereas Chang and Harrington (2010) derive the same conditions with leniency.

2.2 HMM for Cartel Births and Deaths

HMMs provide a means to study dynamic processes that are observed with noise.[11] The evolution of the population of cartels matches this description, because we typically observe the (collusive) dynamics of an industry only irregularly, if at all, and only for discovered cartels. A HMM consists of an underlying hidden ("unobserved") process and an observation process. In particular, the observed data, O_{it}, for industry $i = 1, ..., N$ and periods $t = 1, ..., T_i$ follow a HMM if the hidden states, $\{Z_{it}\}_{t=1}^{T_i}$, follow a Markov chain and if, given Z_{it}, observation O_{it} at time t for i is independent of the past and future hidden states and observations (see Appendix A for a more detailed description). In our case, the hidden process is the state of the industry and the observation process is what the researcher knows about the state of the industry in a given period. The dimension of the state space of the hidden process is typically either assumed or estimated. In our case, it follows directly from economic theory and the institutional environment.

2.2.1 Hidden Process for Cartel Births and Deaths

Consider cartel births and deaths in industry i at time $t > 1$. If the industry is not in a cartel at the beginning of a period, it can try to form a cartel with probability κ_{it}, as outlined above. Conditional on the opportunity, the cartel is stable and becomes operational with probability H_{it}. If the industry is in a cartel at the beginning of period t, then it stays alive with probability H_{it}. With probability $1-H_{it}$, an existing cartel breaks down during period t. We link the probability of cartel dissolution to the ICC, given in (2), but other interpretations (e.g., internal disagreements, entry) could also be given.

[11] Our model belongs to the class of finite Hidden Markov Models (e.g., Cappé, Moulines and Rydén 2005, pp. 6).

This process for cartel births and deaths means that at the end of period t, industry i is either not in a cartel ("n") or is in an on-going cartel ("c"). Treating these two outcomes as the states of hidden process for Z_{it}, its state space is $S_Z = (n, c)$. The associated transition matrix $\mathbf{A}_{it}$ is

$$\mathbf{A}_{it} = \begin{bmatrix} a_{it}^{nn} & a_{it}^{nc} \\ a_{it}^{cn} & a_{it}^{cc} \end{bmatrix} = \begin{bmatrix} (1-\kappa_{it}H_{it}) & \kappa_{it}H_{it} \\ (1-H_{it}) & H_{it} \end{bmatrix} \tag{3}$$

The elements of the matrix are the transition probabilities of a first-order Markov chain. The cell in the upper left-corner, for example, gives $P(Z_{it} = n|Z_{i,t-1} = n)$=$1 - \kappa_{it}H_{it}$.[12]

To complete our specification of the hidden process for cartel births and deaths, let the R.H.S. of (2) vary over industries and time and rewrite the inequality by subtracting from both sides the mean of the expected profits under collusion in industry i during period t (μ_{it}). This leaves a demeaned profit shock, $\pi_{it} - \mu_{it}$, to the L.H.S. of the inequality, which now takes the form of a discrete choice equation with a particular structure on the R.H.S. With H_{it} denoting the probability that the inequality holds for industry i in period t, we have

$$H_{it} = H_{ICDM}(\phi_{it}^* - \mu_{it}) \tag{4}$$

where $H_{ICDM}(\bullet)$ refers to the c.d.f. of the demeaned profit shock. We can think of $\phi_{it}^* - \mu_{it}$ as a function of observable characteristics (which could enter, e.g., through μ_{it}) and the structural parameters of the model.

[12]It is derived as follows: If an industry is not in a cartel at $t-1$, then with probability $(1-\kappa_{it})$ there is no opportunity to form a cartel. If there is an opportunity, the newly born cartel may turn out to be unstable. The probability of this event is $\kappa_{it}(1-H_{it})$. The probability given in the upper left-corner cell is the sum of the probabilities of these two events.

2.2.2 Observed Data and the Observation Process

Our cartel data is incomplete. We therefore postulate that in each period t, the state of industry i is either not known ("u"), or the industry is observed not to be in a cartel ("n") or to be in an on-going cartel ("c"). These three observed cartel outcomes give the state space of the observation process, $S_O = (n, c, u)$.

Our HMM links the observed data to the hidden process that governs the formation and dissolution of cartels. When the unobserved state of industry i at time t is $k \in S_Z = (n, c)$, the probability of observing $w \in S_O = (n, c, u)$ is

$$b_{it}^{k}(w) = P(O_{it} = w | Z_{it} = k). \tag{5}$$

To derive the observation probabilities explicitly and to match them with the institutional environment, we make the following assumptions:

First, we assume that if an industry is not in a cartel, its (true) state is observed in the data available to the researcher with probability $b_{it}^{n}(n) = \beta_{it}^{n}$. If this event happens, $O_{it} = Z_{it} = n$. With the complementary probability $b_{it}^{n}(u) = 1 - \beta_{it}^{n}$, the state cannot be determined reliably and remains unknown. If an industry is in a cartel, its (true) state is observed in the data with probability $b_{it}^{c}(c) = \beta_{it}^{c}$. In this case, $O_{it} = Z_{it} = c$. Again, with the complementary probability, the status remains unknown.

This formulation of the observation process relies on the assumption that if an industry is (is not) in a cartel, the observed data never wrongly suggest that it is not (is). This assumption imposes $b_{it}^{n}(c) = b_{it}^{c}(n) = 0$. We stress that this restriction may sound stronger than it is, because if and when one has reasons to suspect that there are such errors, the status of an industry can be labeled "unknown".[13] The resulting observation probability matrix $\mathbf{B}_{it}$ is

[13] Moreover, this assumption can be relaxed if the data contain information about potential mistakes or mislabelings in the records. See Section 5 for an example.

$$\mathbf{B}_{it} = \begin{bmatrix} b_{it}^{n}(n) & b_{it}^{n}(c) & b_{it}^{n}(u) \\ b_{it}^{c}(n) & b_{it}^{c}(c) & b_{it}^{c}(u) \end{bmatrix} = \begin{bmatrix} \beta_{it}^{n} & 0 & 1-\beta_{it}^{n} \\ 0 & \beta_{it}^{c} & 1-\beta_{it}^{c} \end{bmatrix}. \tag{6}$$

Because $\beta_{it}^{n}\leq 1$ and $\beta_{it}^{c}\leq 1$, the model explicitly allows for the possibility that there are holes in our data. There are two primary reasons for such incompleteness: On the one hand, information about the state of a registered cartel can be incomplete over time. On the other hand, some cartellized industries were never registered and some industries may not have had cartels. For these cases, our data conservatively assign state u, as we explain in greater detail below.

2.2.3 Identification and Estimation

The identification of (the parameters of) a general finite HMM follows from the identifiability of mixture densities (see Cappé, Moulines and Rydén 2005, pp. 450-457). The parameters of our HMM are identified for two further reasons: First, the theoretical model describing the formation and dissolution of cartels allows us to circumvent the problem of identifying the dimension of the hidden process. It directly suggest that $S_Z = (n, c)$. A second source of identification are the parameter restrictions that we impose on $\mathbf{B}_{it}$.

An intuitive way to think about the identification of our HMM is that we have only 2+2 probabilities that call for identification, but a greater number of moments (transitions) that identify them. The observed transitions from c to c and c to n identify H_{it}, whereas the observed transitions from n to c and n to n identify κ_{it}. Finally, the ratios of c to u and n to u identify β_{it}^{c} and β_{it}^{n}.

To derive the likelihood of the HMM, we take two steps. First, we assume an initial distribution for Z_{i1}, i.e. the probability that unit i is in the unobserved state $k \in S_Z$ in the initial period:

$$\tau_i^k = P\left(Z_{i1} = k\right). \tag{7}$$

Second, we let Θ denote the model parameters, $\mathbf{D}_{i1}$ a (2×1) vector with elements $d_{i1}^k(w) = \tau_i^k b_{i1}^k(w)$, $\mathbf{D}_{it}$ a (2×2) matrix with elements $d_{it}^{jk}(w) = a_{it}^{jk} b_{it}^k(w)$ for $t > 1$, and $\mathbf{1}$ a (2×1) vector of ones. The likelihood for the whole observed data can then be written as (see e.g. Zucchini and MacDonald 2009, p. 37 and Altman 2007)

$$L(\Theta; \mathbf{o}) = \prod_{i=1}^{N} \left\{ \left(\mathbf{D}_{i1}\right)' \left(\prod_{t=2}^{T_i} \mathbf{D}_{it} \right) \mathbf{1} \right\} \tag{8}$$

where $\mathbf{o}$ denotes the data (the realization of $\mathbf{O}$).[14]

Four comments about the HMM and its estimation are in order: First, while the maximization of $L(\Theta; \mathbf{o})$ may be a non-trivial matter, (direct) numerical maximization methods can be used (Zucchini and MacDonald 2009, Chapter 3; Turner 2008). Typically, a normalization (scaling) is used to avoid numerical underflow. Second, because $\{\tau_i^n,\ \kappa_{it},\ H_{it},\ \beta_{it}^c,\ \beta_{it}^n\}$ are all probabilities, a simple way to parametrize them is to assume a standard probability model for each of them. Third, estimation of the parameters of H_{it}, as given by (4), can take two routes. One way to proceed is to estimate a reduced form of this probability. The other possibility is to estimate H_{it} structurally, but this requires that the fixed point with collusion (Y^*) and the associated threshold (ϕ^*) are computed.[15]

[14] Picking the appropriate elements from $\mathbf{A}_{it}$ and $\mathbf{B}_{it}$, we can determine $d_{it}^{jk}(w) = a_{it}^{jk} b_{it}^k(w)$ for $t > 1$, i.e., the elements of matrix $\mathbf{D}_{it}$ of the likelihood function that is given as equation (8). If, for example, $o_{it} = c$, the upper left-corner cell of $\mathbf{D}_{it}$ is $d_{it}^{nn}(w) = a_{it}^{nn} b_{it}^n(c) = 0$. For $t = 1$, the elements of the vector $\mathbf{D}_{i1}$, $d_{it}^k = \tau_i^k b_{i1}^k(w)$, in the likelihood function can be determined similarly.

[15] The estimation routine could be e.g. a nested fixed point algorithm where one starts from some initial values for the estimated parameters, calculates the fixed point (i.e., the value of ϕ^*), proceeds to re-estimate the structural parameters by ML, and continues until convergence is achieved. Natural candidates for initial values would be the parameter estimates from a model where H_{it} has been modeled in reduced form. An issue one would have to solve is how

Finally, the HMM summarized above can in principle be extended to allow for unobserved heterogeneity. The HMM literature (see e.g. Altman 2007) has thus far introduced unobserved heterogeneity only into models that lack the theoretical structure of our HMM. To bring in unobserved heterogeneity properly into our HMM would require modeling it within the theoretical model. This extension is beyond the scope of this paper.

2.2.4 State Prediction

A convenient feature of HMMs is that the hidden states of the underlying Markov model can be analyzed in a relatively straightforward way (see Appendix B for a more detailed description of some of these methods). The HMM allows for example for period-by-period inference about the state of the Markov chain that is most likely to have given rise to the observed data for a given industry in a given period. This procedure is called 'local decoding'. In a cartel application, this feature means that one can deduce the likelihood for the existence of a cartel in a given industry for those periods for which the observed data are not directly informative about the state of that industry (i.e., the u's).

3 The Institutional Environment and Data

3.1 The Institutional Environment and the Cartel Registry

The Finnish institutional environment vis-á-vis cartels mirrors wider European and especially Swedish developments both before and after WWII. Before the war there was no competition law. The apparent reason was the prevailing

to deal with the potential multiplicity of Y^*. See CH for a discussion of multiple equilibria in their model. Alternatively, the recently introduced MPEC algorithm could be utilized (Judd and Su 2010).

liberal view which held that contractual freedom entailed also the right to form cartels (see Fellman 2008, 2009). This view started to change in 1948 when a government committee was set to provide a framework for competition legislation. We focus on the developments after 1950, because the heavy wartime regulations were mostly lifted by early 1950s.[16]

The first cartel law, effective from 1958, was built around the idea of making cartels public through registration. Registration, however, was to be done solely on authorities' request. Only tender (procurement) cartels became illegal, and even these were apparently not effectively barred from operation (Purasjoki and Jokinen 2001). Vertical price fixing could be banned if deemed "particularly harmful". The law embodied the prevailing thinking of cartels not (necessarily) being harmful. A Finnish CA was set up to register the cartels. Here Finland followed Norway and Sweden, which set up similar registers in 1926 and 1946.

The CA sent out 9750 inquiries by 1962 and registered 243 cartels (Fellman 2009). However, the fact that registration was dependent on authorities' activism was an issue. To tackle this, the law was slightly revised in 1964. Those cartels that established formal bodies, such as associations, now had to register, but cartels without formal organizations were still exempt from compulsory registration. The law was again revised in 1973. The single largest change appears to have been that the obligation to register was again widened. Finland finally edged towards modern competition law with a committee that started its work in 1985, resulting in a new law in 1988. This law gave the newly established Finnish Competition Authority (new FCA) the right to abolish agreements that were deemed harmful. The law also abolished cartel agreements' status as legally binding contracts. The new FCA initiated a negotiation round with cartels where these were asked to provide reasons why they should be al-

[16]See. e.g. Väyrynen (1990, pp. 69): "The wider public will remember 1954 as the year when the remaining regulations were abolished".

lowed to continue. In 1992 the law was again changed (and took effect in 1993): Only now did cartels become illegal.

The former and current Director Generals of the Finnish CA (Purasjoki and Jokinen, 2001) sum up the environment prior to the 1988 law: "Time was such that there seemed no need to intervene even in clear-cut cases, especially if they had been registered. Registration had been transformed into a sign of acceptability of the [cartel] agreement, at least for the parties involved [in the cartel]".[17] Based on this, we end our analysis to 1990.

3.2 Data Sources and Description

Our data come from three main sources, Statistics Finland, The Research Institute of the Finnish Economy and the Finnish Cartel Registry. The first provides us with 2-digit ISIC level industrial statistics, the second provides us with GDP and trade figures, and the third is our sole source of cartel data.

3.2.1 Registry and Sample

Over the period of its existence the Finnish Cartel Registry registered 900 cartels. For each cartel, there is a folder containing the entire correspondence between the Registry and the cartel (members). For many cartels, the cartel contract is also available. In addition to information on the entry into and exit from the Registry, this information allows us to pin down the actual birth and/or death dates of some cartels and/or their (non-) existence in certain industries and years. The Registry also assigned a 4-digit ISIC type of code to each cartel. Our unit of analysis is a 4-digit ISIC manufacturing industry. While not optimal, data constraints unfortunately prevent an analysis at a more detailed level (e.g.

[17] Purasjoki and Jokinen (2001) mention a few cartels that were not registered, but they do not explain how these cartels were exposed (apart from them being exposed as part of the negotiation initiative set up by the new FCA in the late 1980s). This nevertheless confirms that the Registry was not complete.

at regional and/or product level). To ameliorate problems arising from this, we concentrate on nationwide manufacturing cartels. The total number of 4-digit manufacturing industries in Finland is 234, and we follow them from 1951 to 1990.

Given that archive work is both time consuming and expensive, the paper archive of the Registry large and the number of cartels high, we didn't have the option of including all manufacturing cartels in our sample.[18] Our sample of cartels consists of the first registered horizontal cartel from each manufacturing industry.[19] We end up including 109 cartels.

While this sampling scheme may appear to introduce a potential problem due to us not including potential later cartels, this is not the case: Our HMM model by design allows for incomplete sampling. As explained below, the later cartels in an industry where another cartel existed earlier do not call for a treatment different from those (potentially existing) cartels in industries where no cartel was ever registered.

3.2.2 The Definition of States

The Registry contains information on seven types of events that the registered cartels (may) have experienced between 1951-1990. First, we know for all the registered cartels the date when they entered the Registry ('register birth' - t^{rb}). For many cartels we know when they exited the Registry ('register death' - t^{rd}). The Registry also has occasionally information on a cartel changing its contract ('contract change' - t^{cc}), such as an addition of members. There can

[18]We have been through the folders using a "semi-structured" approach: After initial discussions on what it is that we want to record, we randomly chose 8 cartels and had 4 researchers (including two of us) go independently through the material to establish whether the information we sought was available, and if, how to record it. We then checked the 4 individuals' records against each other, and decided on a common approach and interpretation of e.g. various wordings that we encountered. We then followed a written protocol in collecting the information.

[19]In the rare cases when cartels were registered simultaneously, we checked that they indeed are separate cartels and if so, included them into the sample.

be many such events per cartel. For some cartels, we can establish their actual birth ('birth' - t^b) and/or the death date ('death' - t^d). In addition, there were incidences where a cartel was observed to be operational prior to the registered birth ('actually alive' - t^{aa}) and also some incidences where we found proof of the cartel being alive after their registered birth and before their (registered) death ('still alive' - t^{sa}).

We use these events to define what the observed state of industry i is in year t. The observation state space is $S_O = (n, c, u)$ and we assign all industry-year observations into one of these states. How we do this is illustrated in Figure 1. Keep in mind that our interpretation of state c is (in line with CH) that not only was there a cartel agreement in place, but also that the cartel was active. Similarly, state n is interpreted to mean competition. Any observation that cannot be given such an interpretation is assigned into state u. This mechanism means that if an industry does not show up in the Registry at all, all observations for it are assigned into u.

[Figure 1 – Time-line for state-definition and observed cartel incidences here]

Cartels for whom we observe the actual birth date t^b or for whom we have information on the cartel being actually alive some year prior to register birth (t^{aa}) are assumed to be alive between t^b (t^{aa}) and the date of register birth (t^{rb}). Correspondingly, cartels for whom we know the actual death date (t^d) are presumed to be dead between t^d and the date of register death (t^{rd}). In addition, cartels are assumed to be alive every year where we observe an active move, i.e., a 'still alive' or a 'contract change' incidence. We assume that a cartel for which we can pin down the actual death date is alive the year before. Finally, cartels are assumed dead the period prior to actual birth. For all the other periods, the state of the observation process is u (unobserved).

The definition of the observed states is in our view quite conservative. For instance, even though the Registry effectively assumed that the cartels were alive between t^{rb} and t^{rd}, we only assign an industry into state c when an event like t^{sa} or t^{cc} appears. The reason for including the periods between t^{b}/t^{aa} and t^{rb} as observed c-states is due to the assumption that when a cartel is asked to register (at t^{rb}), it had no reason to tell any other birth date but the latest. Correspondingly, when the Registry finds out that the cartel is dead (t^{rd}), there is no incentive for the cartel not to inform the Registry of an actual restart between t^{rb} and t^{rd} when confirming their death to the Registry. We hence record them as n. Note also that the way in which we define observed/unobserved states here removes the usual problem of right censoring for cartels where we do not know the ending date.

Combining the 109 industries appearing in the Registry with the 125 industries that never entered it, we end up with a HMM data such that $N = 234$ and $T = 40$, with the following features: First, for 939 (industry-year) observations we know the actual status of the cartel. Second, 365 of these observations are not in a cartel (n-states) and 574 are in a cartel (c-states). For the remaining 8421 observations the status of the industries is unobserved.

3.2.3 Observed Transitions and Duration of Cartels

We have more cartel observations (c-states) during the first 15 years of the Registry's existence, with a peak in 1959. In this period we have few "no cartel" observations (n-states). In contrast, the annual share of n observations is double the share of c observations during the early eighties. A naive approach to estimating the prevalence of cartels and how it has evolved over time would use the ratio between observed c- and n-states. This approach is fundamentally flawed for two reasons. First, it neglects the fact that most of the time we do not know whether there is a cartel or not in a given industry. Second, it ignores inter-temporal variation in the ratio of c- (and n-) states to u-states.

In Table 1 we show the transitions from period $t-1$ to period t that follow from our definitions of the three (observation) states. The difference between considering the cartelized industries only and all the industries is that in the latter case, we observe a lot more transitions from u to u. For those industries with a registered cartel, 78% of the observations are transitions from u to u whereas in the whole data, the proportion is 90%. Adding the industries that do not have an exposed cartel obviously yield no more information on transitions from state n to c or vice versa, but crucially, do affect the cell probabilities.

[Table 1 – Observed transitions here]

In the prior literature, register data are often assumed to be roughly in line with the underlying true distribution of cartel births and deaths. Clearly this is not the case in our data: The representative cartel was on average born 3.6 years earlier than it was registered and died 2.6 years earlier than it exited the Registry. If the Registry dates were used, we would find too few short lived cartels due to late registration of cartel deaths. The adjusted birth and death dates suggest that the modal cartel lives for 4-6 years, echoing Levenstein and Suslow's (in press) analysis of 81 illegal international cartels. However, the mean adjusted duration of our legal cartels (13 years) is somewhat longer than what others studying illegal cartels have found. The closest study to ours is Jacquemin, Nambu and Dewez (1981) who, studying legal Japanese export cartels, find an average duration of 10 years.

3.2.4 Explanatory Variables

We use four types of explanatory variables: Variables describing 1) how the Registry worked; 2) the macroeconomic environment; 3) the industries; and 4) the Finnish foreign trade. We describe them below and provide summary statistics in Table 2.

[Table 2 - Descriptive statistics here]

Workings of the Registry

The ability of the Registry to detect the births and deaths of cartels may have varied over time. To accommodate this and to control for our sampling scheme, we make the two observation probabilities (β^c_{it} and β^n_{it}) each a function of two variables: First, we let β^c_{it} (β^n_{it}) vary with the number of cartels that entered (exited) the Registry in year $t-1$. Second, we allow β^c_{it} (β^n_{it}) to be a function of the (once) lagged cumulative number of registered births (deaths). These variables are denoted ($Birth{-}flow, Birth{-}stock, Death{-}flow, Death{-}stock$) and they are computed using the data from the whole Registry with 900 cartels.[20] As shown in Appendix C, there is a weak negative trend and a lot of variation over time in the total number of annually registered cartels. There is an upward trend in the number of Registry deaths.

[20]Our sampling scheme means that after the register death of a cartel, the probability of observing a cartel in the same industry is zero. Another feature of the data is that by design, we have very few observations of a cartel not existing (state n) prior to the Registry being established. This implies that the (estimated) probability of observing state n should be small prior to the Registry starting to operate. We could impose these constraints in the estimation. We instead allow the observation probabilities β^c_{it} and β^n_{it} to vary over time in a flexible way and check that the estimated probabilities are consistent with these particularities of our sampling scheme.

Macroeconomic Demand Fluctuations

There is a large cartel literature focusing on the importance of demand and business cycle fluctuations for cartels. Most notable are Green and Porter (1984), whose model suggests that price wars will arise in response to unobserved negative demand shocks, and Rotemberg and Saloner (1986), whose model predicts price wars during booms (later discussed by e.g. Haltiwanger and Harrington 1991). The literature suggests that cartel formation may be linked to the growth trend as well as to idiosyncratic changes in demand not anticipated by the cartel (Jacquemin, Nambu and Dewez 1981 and Suslow 2005).

We have a long panel with 40 years of data over a period in which the Finnish macroeconomy went through large business cycle changes. To utilize this variation, we include macroeconomic variables into the HMM. We detrend the GDP volume index using the Hodrick and Prescott filter (Hodrick and Prescott, 1997), decomposing GDP into the long run growth trend ($HP-trend$) and deviations from the long run trend. We decompose the deviations into two variables, one capturing positive deviations from the long run trend ($GDP-pos$), and another capturing all negative deviations from the long run trend ($GDP-neg$).[21] Time series of these variables are displayed in Appendix C.

Industry Characteristics

Several authors have focused on the importance of industry characteristics when explaining cartel formation. Slade (1989, 1990) suggests, for example, that price wars can arise from changes in industry characteristics. Cartel members' knowledge of fundamental structural parameters may be incomplete, and industry specific shocks (e.g., negative sales shocks) may change the equilibrium

[21]Detrending was done using a smoothing index of 100. Note that both deviations are defined in absolute terms.

prices. We therefore include the gross value of production over time (GVP), as measured at the level of 2-digit industries.[22] Among others, Bradburd and Over (1982) argue that organizational costs of both cartel formation and maintenance are expected to increase with the number of firms in an industry. We do not have an ideal measure for the number, but can nevertheless include the number of plants, as measured at the 2-digit level ($Plants$). We also include the ratio of raw material expenses to the gross value of production ($Materialshare$) as a measure of (average) variable costs of production. The ratio of blue collar working hours to the gross value of production ($Hours/GVP$) is a measure of (the inverse of) labor productivity.

Trade Variables

As Finland is a small open economy, both imports and exports are potentially important factors influencing cartellization. The average GDP-share of foreign trade (=exports+imports divided by GDP) was 32.1%, calculated over our sample period. Export shocks can be thought of as analogous to demand shocks in their effects on cartellization. Imports are a source of competition for domestic firms and therefore would be expected to have a similar impact as a lowering of entry barriers. Exports (imports) grow during our sample period on average 4.2 (5.1) per cent a year, with some sizable short term fluctuations.

A peculiar feature of Finnish foreign trade, to which we turn in more detail below, is the important role played by bilateral trade with the Soviet Union which averaged 17% of all exports over our sample period. There were also important institutional changes in the foreign trade with the market economies, with Finland joining (the European Free Trade Area) EFTA as an associate

[22] We use 2-digit ISIC data because of difficulties in tracking industries across three changes in the 4-digit industry definitions that take place during our observation period. As the data was not available in electronic form, we collected data for every 4th year and interpolated the values in between.

member in 1961 and as a full member in 1986, and signing a free-trade agreement (which abolished custom duties starting 1977) with the EU in 1973. We use deflated goods exports (*Exports*) and goods imports (*Imports*) as our trade variables. We display the time series for these variables in Appendix C.

4 Empirical Analysis

4.1 Parameter Estimates

Our legal era HMM is estimated with ML, using the likelihood function (8). We parametrize the transition and observation probabilities as single index functions. This means, for example, that we impose $\kappa_{it}= \Phi\left(\kappa'\mathbf{x}_{it}\right)$, where $\Phi(\bullet)$ is the c.d.f. of the normal distribution, $\mathbf{x}_{it}$ denotes the explanatory variables and κ is the parameter vector to be estimated.[23] Note that the theoretical model on which we build is stationary, but our HMM is not. The covariates allow both for temporal (e.g., secular growth and business cycles) and cross-sectional variation.

We present the main estimation results in Tables 3 and 4: In both tables, Model 1 includes only macro covariates (third order polynomial of $HP-trend$, and the GDP deviations) for H_{it} and κ_{it}, Model 2 includes also the industry characteristics, and in Model 3 we add trade variables. The observation probabilities are in all models linear in the two flow variables and quadratic in the two stock variables. The initial condition τ^n is always estimated.

[Table 3-4 - Estimation results here]

[23] Given that there are no modern competition policy parameters that could enter the ICC in our data (due to cartels being legal), the gain from estimating H_{it} structurally is very minor. In particular, we lack knowledge of the values of the competition policy parameters, rendering the execution of a meaningful counterfactual exercise impossible. We therefore estimate a reduced form of it.

Starting with H_{it} (Table 3), we find that all the coefficients of $HP - trend$ are significant, suggesting a nonlinear relationship between the level of GDP and the probability of the ICC holding. In five out of six cases, both types of shocks to GDP affect the probability of the ICC holding positively. Adding industry variables (Model 2) has very little effect on the macro variables and none of the industry characteristics are significant. In Model 3, exports carry a negative and significant, imports a positive and significant coefficient. While the former, at least when interpreted as a positive demand shock, is in line with the Chang and Harrington (and Lee and Porter) style arguments, the latter is on the face of it unintuitive as it suggests that increased competition increases the probability of a cartel. Including the trade variables has some effect on the other variables' coefficients. Notably, the coefficient on the negative GDP shocks increases, and the coefficient of material share becomes significant.

Turning then to κ_{it}, we find in Model 1 that the polynomial terms of $HP - trend$ all carry coefficients that are smaller in absolute value than those for H_{it} and mostly insignificant. Positive (negative) shocks to GDP affect cartel formation positively (negatively). Adding the industry characteristics doesn't change these results: Gross value of production and material share both obtain a negative and significant coefficient. In Model 3, the trade variables are insignificant and do not affect the coefficients of the other variables.

We display the parameters of the observation probabilities β^c_{it} and β^n_{it} in Table 4. The flow variable is significant only in β^n_{it}. The parameters of all the stock variables are significant in both processes, meaning that both β^c_{it} and β^n_{it} are nonlinear functions of the stocks. This suggests that they may indeed control for the effects of our sampling scheme (see also Figure 2 and the related discussion below).

The final parameter we estimate is the initial probability of not being in a cartel (τ^n). It turns out to be 95%. This high probability may be explained by the fact that in 1951, the very strict war-time regulations that had been in place more or less since end of 1939 had only recently been lifted.

Likelihood ratio tests suggest that the restricted specifications are rejected against the more general alternatives. Model 3 is therefore our preferred model.[24] We study its robustness below.

4.2 Cartel Dynamics

4.2.1 Dynamics of κ, H, β^c and β^n

We can calculate the probability of forming a cartel (κ_{it}) and the probability that the ICC (H_{it}) holds for each industry-year observation in our sample. The means over the years and industries are reported on the last row of Table 3. We find that on average, κ_{it} is round 0.2. The interpretation of this estimate is that an industry that was not in a cartel last year has a 20% chance of being able to form a cartel this year.

In contrast, the estimated probability of the ICC holding (H_{it}) is on average 0.9 or higher. The implication of this is that when cartels are legal, i) industries form a cartel with a high probability *if* they get the chance and ii) that cartels, once formed, are very durable. This estimate of ours is very close to that obtained by Ellison (1994) studying the stability of a single U.S. cartel, the Joint Executive Committee.

In Figure 2 we show the development of the cross-industry means of the predicted H_{it} and κ_{it} for our preferred Model 3. The predicted probability of

[24]The literature on testing the fit of HMM models is rather thin; see ch. 6 in Zucchini and MacDonald (2009). This applies in particular to models with a discrete observed state space, such as ours. One way to extend the model would be to allow for a higher-order Markov chain. However, according to Zucchini and McDonald (pp. 119), the number of parameters of such a model rapidly becomes prohibitely large.

continuation is high, but exhibits a period of lower values between mid-1950s and early 1970s before returning to levels above 0.9. The opportunity probability (κ_{it}) varies more and exhibits a positive trend. The large increases in early 1970s, early 1980s and late 1980s seem at first glance to be due to the large positive shocks in the aggregate demand in these periods. Notice, however, that κ_{it} is increasing trend-like, so even ignoring the effect of the positive GDP shocks, its value is significantly higher at the end of our sample period than at the beginning of it.

[Figure 2 - Development of H, κ, β^c and β^n]

The observation probabilities, β^c_{it} and β^n_{it} , are also displayed in Figure 2. Their time-series show that the probability of observing an existing cartel starts very high and ends being very small, while the reverse happens to the probability of establishing that a cartel does not exist. Two features of the Figure are reassuring in light of our sampling scheme: First, given that the Registry started in 1959, there is essentially a zero probability of us observing that a cartel does not exist prior to 1959. This is indeed what we find. Second, given that we only included the first cartel in any given industry into our sample, the estimated probability of detecting a cartel should decrease over time, which it does (see fn. 20).

4.2.2 Dynamics of the Degree of Cartellization

The above results suggest that the degree of cartellization may have increased over our sample period. We use the HMM structure of our model to illustrate this in two ways. We employ both a recursive calculation of $Pr[Z_{it} = c]$ and a modified local decoding method to analyze the hidden states and estimate the proportion of manufacturing industries that had a cartel in a given year. The recursive calculation is made individually for each industry (see Appendix B). The modified local decoding works for each industry as follows: First, the conditional probability of the hidden state being c or n given the observed data is calculated for each year. Second, local decoding assigns to each year that hidden state which has the highest conditional probability. Using this probability, we assign each u-observation a probability of the hidden state being c (or n).[25]

The results of this exercise, averaged over the industries and years, show that the proportion of manufacturing industries that had a cartel is close to 50%. The time-series are displayed in Figure 3. The two methods produce very similar results: The proportion of cartellized industries starts reasonably low at round 6%, reflecting the high value of τ^n and the low values of κ_{it} in the early years. It then starts to increase, and jumps upwards in the early 1970s when both κ_{it} and H_{it} increase. The former has an increasing trend and a large spike in the early 1970s. The latter starts increasing around 1969 after having declined since the mid-1950s.

[Figure 3 - Estimated proportion of cartellized industries]

Inferring the dynamics of cartellization directly from the Registry data is impossible. This is clearly displayed in Figure 3 where we show both the proportion of c-observations in the observed ("raw") data, and the proportion of c-observations that result from our local decoding exercise. These (almost) co-

[25] Our adjustment to local decoding is that we assign probabilities, whereas local decoding assigns ones and zeros. While that approach is natural e.g. in speech recognition, in our application it would amount to throwing away information. For instance, it would assign the hidden state c for two observations where for the first, the probability of the hidden state really being c is 0.51, and for the other 0.98. Note also that given our assumptions about the observation process, each of the observations for which we observe c (n) is assigned c (n) in the local decoding exercise.

incide during the early years of the observation period, and then diverge, with the estimated proportion of cartellized industries increasing and the proportion of c-observations in the raw data decreasing.

Coupling Figure 3 with the development of the observation probabilities β_{it}^{c} and β_{it}^{n} shown in Figure 2 explains the divergence between the raw data and the estimated proportion of cartellized industries. Early on in the observation period, any industry in hidden state c is almost surely observed to be in that state as β_{it}^{c} is very high. At the time β_{it}^{c} starts to decline - meaning that a lower and lower proportion of observations in hidden state c are observed to be in that state - the two c-series start to diverge. A similar but reverse story holds for the n-series. This also makes clear why one cannot make inference on the degree of cartellization from the raw data alone: One needs to couple it with a model of cartel behavior and a model of the observation process, i.e., a HMM model like ours.

Figure 3 suggests a rather dramatic story, with the degree of cartellization in Finnish manufacturing growing over time and reaching very high levels by the end of the 1980s. In addition, Figures 2 and 3 suggest that the rapid increase in the degree of cartellization may be driven by the spike in κ_{it} in the early 1970s, and the upward trend in H_{it} during the same period. The spikes in κ_{it} and the trend in H_{it} beg three questions: First, are they due to misspecification of the model in one way or the other? Second, to what extent do they drive the high level of cartellization reached by the end of 1980s? Third, are there any economic explanations for them? We discuss these three questions in the next subsection.

4.3 Robustness and Discussion

4.3.1 Robustness Tests

We probe the robustness of our results from Model 3 in five dimensions:

First, we examine the effect of the initial condition on our results. We allow for heterogeneity across industries in the initial probability of not being in a cartel by including the industry characteristics (measured in 1951) in τ^n. The industry characteristics are neither individually nor jointly significant. The estimated mean of τ^n is very close to that reported for Model 3 in Table 4 and varies from 0.90 to 0.98. However, Finland had a tradition of export cartels that started prior to WWII (Kuisma 1993, Fellman 2008). This tradition could have led to the formation of domestic cartels by the beginning of our sample period. The estimated τ^n may therefore seem high. To probe this, we impose a lower value for τ^n (0.5) to allow for a higher degree of cartellization in 1950. Our main qualitative results remain intact except for the naturally occuring increase in the predicted rate of cartellization in the first few years.

Second, we consider three specifications for the observation probabilities β^c_{it} and β^n_{it}: We introduce industry characteristics to allow for cross-industry heterogeneity and allow for richer dynamics by including the third order polynomials of the birth and death stock variables. Finally, we let the observation probabilities reflect the changes in the Finnish cartel legislation and registration obligations, introducing three indicators corresponding to the law changes taking place in 1958, 1964 and 1973. The results echo our main findings.[26]

Third, since it is not obvious how we should include the trade variables, we try different specifications for them (see also fn. 29). For instance, we estimate Model 3 including total trade and the share of imports of total trade in κ_{it} and

[26]There is a convergence problem with the last model using the law change dummies. The problem disappears when we slightly change the base specification.

H_{it}. In most specifications, trade variables are significant only in H_{it}. However, the overall results stay the same.

Fourth, we try different specifications of business cycle dynamics. To allow for non-linearities in the responses to business cycle shocks we include also the squared terms of $GDP - pos$ and $GDP - neg$. To check for the robustness of using the Hodrick and Prescott filter we remove the filtered variables and use the third order polynomial of unfiltered GDP instead. Again, the dynamics and levels of κ_{it} and H_{it} remain intact, including the jump in κ_{it}.

Finally, we re-estimate our HMM using data only on the 109 industries with a known (= registered) cartel during the sample period. This test allows a more direct comparison to most of the existing work that only uses data on industries that have had an exposed cartel. The results are very much in line with those reported above, suggesting that in our case, not using data on industries which do not have a known cartel would not bias the results greatly. This finding, together with the above specification checks of the observation probabilities, suggests that our estimates of the rate of cartellization ought not to be driven by differences between the industries for which there is a registered cartel and the industries that never entered the Registry. Whether these observations extend to other data sets is naturally an open question.

4.3.2 Counterfactuals

While the spike in κ_{it} plays an important role, its upward trend is much more important. This is due to the high continuation probability H_{it} which means that there was very little outflow from the stock of cartels.[27] We perform two

[27] To give an example, let us use the sample averages of $\kappa_{it} = 0.23$ and $H_{it} = 0.90$. These result in a steady state rate of cartellization of 68% with a cartel-birth (death) rate of 7%. Reducing H_{it} to 0.6 (0.4) would result in 26% (14%) of industries being cartellized in the steady state.

counterfactuals that both are designed to shed light on the importance of the spikes in κ_{it}. First, we replace the $GDP-pos$ values of the years 1972-75 with the average of all other years that had a positive shock. Second, we also replace the large shock of 1989 with a (similarly calculated) average.

The relative importance of the GDP shocks is illustrated in Figure 4. It displays the expected proportion of industries that have a cartel using both actual and counterfactual data. All graphs in Figure 4 are produced using the recursive calculation method for $Pr[Z_{it} = c]$ (see Appendix B).

[Figure 4 - Counterfactual]

Using the actual data, the proportion of cartellized industries increases from 34% in 1971 to 94% in 1975 and 96% in 1990. The first (second) counterfactual yields 34% (34%) in 1971, 79% (77%) in 1975, and 96% (95%) in 1990. These counterfactuals show that the large GDP shocks do not drive the high degree of cartellization at the end of our observation period.

4.3.3 Economic Explanations

In this Section we offer possible but necessarily somewhat speculative explanations for the early 1970s jump and trend in κ_{it} and the coinciding increase in H_{it}.

Finland's bilateral trade with the Soviet Union offers one explanation. The jump in κ_{it} coincides almost perfectly with the first oil crisis, which hit the open Finnish economy. The resulting export shock was however positive because it increased bilateral trade with the Soviet Union. Finland paid its Soviet oil imports by exporting manufacturing goods. The growth in bilateral trade was accompanied by a diversification of trade from being mostly ships in the early 1950s to covering a wider set of manufacturing industries by the late 1970s.

The trade between the Soviet Union and Finland was based on a centralized inter-governmental system, and was handled through bilateral clearing accounts (see e.g. Ollus and Simola, 2006 and Fellman 2008). The general terms of trade were agreed at the national level, but the final agreement was an interactive process involving the participating companies. Production alliances were also common (Ollus and Simola, 2006, pp. 20). The process seems to have been conducive for non-competitive behavior and (possibly) cartel formation also in domestic markets.[28]

The negotiations necessitated by the bilateral trade arrangements meant that representatives of Finnish manufacturing firms met more often than they would otherwise have met. This is consistent with an increase in κ_{it}.[29] Both the more frequent interaction and the encouragement for and use of productive alliances may have affected H_{it} by lowering the costs of monitoring other members and improving capacity allocation among the firms.

Another explanation is a structural change in the Finnish economic environment in 1968. That year, the first so-called General Incomes-Policy Settlement between the government, the labor unions and the industry (employers') associations was signed (see, e.g., Fellman 2008). This may have affected H_{it} because it prohibited the indexation of prices to inflation, meaning that the returns to firms agreeing on prices rose. The same agreement may have affected

[28]This has not gone unnoticed in the literature: e.g. Ollus and Simola (2006) conclude (pp. 21): "Finnish exporters to the Soviet Union were protected from external competition which made exporters lazy. The exports favored the less competitive industries and biased the production structure in Finland." See also Schultz (2002), who argues that export cartels facilitate tacit collusion in the domestic markets.

[29]To elaborate on the timing of the jump in κ_{it} we have re-estimated our Model 3 allowing for different specifications of the trade variables in κ_{it}. In particular we divide exports into Russian exports and other exports. Generally we find the same results as before: A strong jump in κ_{it} in the early 1970s. In some specifications, Russian exports obtains a coefficient that is significant at the 10% level.

κ_{it}, because it is generally thought that the collective agreements also increased strength of the labor unions. As a result, the need for firms to coordinate their actions may have grown, meaning more opportunities to form a cartel.

More generally, the trend towards increasing corporatism, reached (according to e.g. Virtanen 1998) its apex in the early 1970s. Virtanen writes (pp. 254): "The 1973 [competition policy] legislation marked the culmination of post-World War II development. Competition policy in the committee report played a subsidiary role as a part of "public price policy". The committee viewed competition policy as complementary to price controls in containing inflation. This seems to have meant that the government either took a relaxed view, or even encouraged price coordination among firms.[30]

Finally, the EEC free trade agreement negotiated from late 1960s onwards and signed in 1973 generated a large change in the institutional environment of Finnish manufacturing firms, creating the expectation of not only increased access to European markets, but also of increased foreign competition in the domestic market. The negotiation process again lead to discussions between the government and the industry, possibly leading to an increase in κ_{it}. The actual agreement may have affected H_{it} for example by the industry feeling the need to form "defensive" cartels whose purpose was to accommodate entry.

4.4 Summary

According to our estimates, the proportion of manufacturing industries that had a cartel was on average close to 50% over our observation period, reaching 90%

[30]According to Virtanen (the Deputy Director General of FCA), "the execution of price controls strongly encouraged firms to establish industry associations entrusted with representing the firms in the price control process and filing common applications for increased prices to be assessed by the price control authorities" (private communication with Virtanen, March 10, 2011). This means that the price regulation authority encouraged firms in a given industry to file common instead of individual applications (for price increases) to the authority.

by 1990. While stark, this result is robust to the various extensions we have tried. Our results make it clear that attempting to infer the rate of cartellization directly from the type of "raw" cartel data we (and other researchers) have is bound to fail, as such an exercise does not take into account the peculiarities of the data generation process.

At a first look, it appears as if our results are driven by spikes in the probability of forming a cartel and a rebound in the probability of the ICC holding. We find explanations for the timing of these two events. Moreover, robustness tests show that our results are not driven by them. The results come about through the interplay of a reasonably high probability of forming a cartel, and a high probability of the ICC holding.

5 Extension: Illegal Cartels and Modern Competition Policy

In modern data sets on discovered cartels (see, e.g., Miller 2009, Brenner 2009, Levenstein Suslow 2006), the observed data vary but are becoming increasingly detailed. To illustrate such data, consider how an illegal cartel is exposed. The first data point that is exposed is that the cartel exists in the period in which it is either uncovered by the CA, or a member applies for leniency. The CA may then extend its investigation into the past of the cartel and eventually, either the CA and / or the court(s) establish the periods in which the cartel has existed. The cartel may have existed for longer or shorter. The CA may be able to establish that in some previous periods the cartel did not exist, or fail to establish (non-) existence in a given period. This observation process may produce data on the cartel's existence for some of the years preceding their exposure. After the investigation, a new cartel may be created in the industry, and the cycle begins again. For a number of industries, the status of the industry cannot be determined for any period. A prime example of such a case is an industry that has never been investigated or convicted for having a cartel.[31]

A great advantage of our HMM approach is that it can easily be tailored to the specifics of the institutional environment. To show how, we outline here briefly a HMM for illegal cartels that allows for a probability of cartel detection, and for a probability of applying for leniency, as in CH. These two probabilities are empirically important because they are key (structural) parameters describing the efficacy of modern competition policy.

5.1 Hidden Process with Illegal Cartels

Assume that there is a CA that constantly monitors the status of each industry. At the end of period t, the state of industry i is detected by the CA with probability σ_{it}. If the industry is in a cartel, the cartel is shut down immediately (and potential fines are levied). If the industry is not in a cartel, the industry stays as is. Besides the CA, there is a corporate leniency program in place. Following CH we postulate that firms resort to the leniency program only if the cartel is breaking up. Conditional on it happening, the probability that the cartel will be exposed to the CA because of a leniency application is ν_{it}.

This process for cartel births and deaths means that at the end of period t, industry i is either not in a cartel ("n"), is in an on-going cartel ("c"), has been detected and shut down by the CA ("d") or has after the break up been exposed to the CA because of a leniency application ("l"). Treating these four outcomes

[31] Appendix D illustrates the type of observed data that this process is likely to generate and to which a cartel researcher might have access.

as the states of the hidden process for Z_{it}, its state space is $S_Z = (n, c, d, l)$. The associated transition matrix $\mathbf{A}_{it}$ is

$$\begin{bmatrix} (1-\kappa_{it}) + \kappa_{it}(1-H_{it})(1-\nu_{it}) & \kappa_{it}H_{it}(1-\sigma_{it}) & \kappa_{it}H_{it}\sigma_{it} & \kappa_{it}(1-H_{it})\nu_{it} \\ (1-H_{it})(1-\nu_{it}) & H(1-\sigma_{it}) & H_{it}\sigma_{it} & (1-H_{it})\nu_{it} \\ (1-\kappa_{it}) + \kappa_{it}(1-H_{it})(1-\nu_{it}) & \kappa_{it}H_{it}(1-\sigma_{it}) & \kappa_{it}H_{it}\sigma_{it} & \kappa_{it}(1-H_{it})\nu_{it} \\ (1-\kappa_{it}) + \kappa_{it}(1-H_{it})(1-\nu_{it}) & \kappa_{it}H_{it}(1-\sigma_{it}) & \kappa_{it}H_{it}\sigma_{it} & \kappa_{it}(1-H_{it})\nu_{it} \end{bmatrix}.$$

The elements of $\mathbf{A}_{it}$ are the transition probabilities of a first-order Markov chain.[32] We have specified $\mathbf{A}_{it}$ with particular assumptions in mind. First, the detection probability σ_{it} shows up only in columns 2 and 3 because we assume that the detection activities of the CA affect only those states in which an industry is in a cartel at the beginning of period t.[33] Second, the first and two last rows are equal, because we assume that if an industry has at $t-1$ been in a cartel that has been exposed to the CA, it does not affect the process that leads to the creation of new cartels in subsequent periods. Both of these assumptions can be relaxed if the institutional environment so requires and/or if the available cartel data are rich enough to permit a more flexible model (e.g. a larger state space).

[32]The cell in the upper left-corner, for example, gives $P(Z_{it} = n|Z_{i,t-1} = n)$=$(1-\kappa_{it}) + \kappa_{it}(1-H_{it})(1-\nu_{it})$ =$1 + \kappa_{it}\,(H_{it}(1-\nu_{it}) + \nu_{it})$. It is derived as follows: If an industry is not in a cartel at $t-1$, then with probability $(1-\kappa_{it})$ there is no opportunity to form a cartel. If there is an opportunity, the newly born cartel may turn out to be unstable, but the member firms do not apply for leniency. The probability of this event is $\kappa_{it}(1-H_{it})(1-\nu_{it})$. The probability given in the upper left-corner cell is the sum of the probabilities of these two events.

[33]The cell in the first row of the third column, for example, gives the probability for the event that an industry that has not been in a cartel at $t-1$ forms a cartel during period t but is immediately detected and shut down by the CA.

5.2 Observation Process

In modern era data sets, the state space of the observation process has to be augmented to $S_O = (n, c, d, l, u)$, where "d" refers to a cartel that has been detected and shut down by the CA and "l" to a leniency application. This kind of observed data can be linked to the hidden process in many ways.

For example, assume that (i) if an industry is (is not) in a cartel, the observed data never wrongly suggest that it is not (is), that (ii) the exposure of a cartel to the CA is observed (by the researcher) with probability one, and that (iii) the observed data never suggest (to the researcher) that a cartel has been shut down by the CA or exposed because of leniency when it really was not. The observation probability matrix would then be

$$\mathbf{B}_{it} = \left[\begin{array}{c} b_{it}^{k}(w) \end{array} \right] = \left[\begin{array}{ccccc} \beta_{it}^{n} & 0 & 0 & 0 & 1-\beta_{it}^{n} \\ 0 & \beta_{it}^{c} & 0 & 0 & 1-\beta_{it}^{c} \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 1 & 0 \end{array} \right],$$

where $b_{it}^{k}(w)$ again denotes the probability of observing $w \in S_O = (n, c, d, l, u)$ when the unobserved state of industry i at time t is $k \in S_Z = (n, c, d, l)$, and $b_{it}^{n}(n) = \beta_{it}^{n}$ and $b_{it}^{c}(c) = \beta_{it}^{c}$. Parameters β_{it}^{c} and β_{it}^{n} reflect the ability of the CA (and courts) to determine, in an ex post investigation, whether a detected cartel did or did not exist in the periods prior to the detection. They are therefore potentially policy relevant.

Other assumptions about the observation process would lead to a different $\mathbf{B}_{it}$. For example, the assumption of no labeling mistakes could be relaxed. We could allow $b_{it}^{c}(n)$ and $b_{it}^{n}(c)$ to be nonzero to be in line with Lee and Porter (1984) and Ellison (1994).[34]

[34] Recall that these authors had demand and cost data.

5.3 Estimation and Identification

The parameters of the extended model can be estimated by ML, using the likelihood function (8). The elements of $\mathbf{D}_{it}$ needed for the likelihood can be derived from $\mathbf{A}_{it}$ and $\mathbf{B}_{it}$.[35]

So far, we have been agnostic about the precise form of H_{it}. If one wants to impose structure to it, the models of CH would give a good starting point. We outline in Appendix D how the ICC condition has to be modified for CA detection and leniency. With data illegal cartels, the returns to structural estimation of H_{it} are likely to be high, as it would allow a number of interesting counterfactual experiments on competition policy.

6 Conclusions

We have shown how the data typically available on cartels yields a Hidden Markov Model (HMM) once it is matched with a theoretical cartel model. HMMs take into account that there is a difference between what is actually going on (the hidden state) in an industry, and what is observed about the industry (the observation state). In particular, HMMs allow for the possibility that the observer/econometrician does not know whether an industry is in a cartel or not at a given point in time. This is a very likely state of affairs for any given observation on a market or an industry. The estimation approach can be merged with various dynamic models of cartel behavior and modified

[35]There are 4+2 probabilities that call for identification in the above HMM, tailored for illegal cartels and an active CA. The intuition of the moments that identify the parameters is as follows: First, the observed transitions from c to c and c to n identify H_{it}, whereas the observed transitions from n to c and n to n identify κ_{it}. Transitions from and to d and from and to l allows one to identify σ_{it} and ν_{it}. Finally, the ratios of c to u and n to u identify β^c_{it} and β^n_{it}.

to fit varying institutional environments. We chose the model of Harrington and Chang (2009, see also Chang and Harrington 2010) because it endogenizes cartel births and deaths. We emphasize that other theoretical models could be used instead.

We have taken our HMM model to data on Finnish legal nationwide manufacturing cartels from 1951 to 1990. We find that the mean probability of getting the chance to form a cartel is around 20%. The probability of the incentive compatibility condition holding is as high as 90%. We estimate the proportion of Finnish manufacturing industries that were cartellized in our sample period and find that the proportion was on average close to 50% and increasing over time. By the end of the period, most industries had a cartel. While stark, these results are robust to various specification tests. Our counterfactual analysis shows that the high rate of cartellization is not generated by the positive GDP shocks forcing a spike in the probability of forming a cartel. We offer potential explanations both for the spike and the simultaneous rise in the probability of the incentive compatibility condition holding. The explanations have to do with changes in the institutional environment of Finnish manufacturing. Taken at face value, our results suggest high returns to effective competition policy even if the welfare losses from Finnish cartels were lower than the typical estimates found in the literature. However, we remain open to the possibility that some of our results are an artifact of our modeling choices.

Last but not least, we have shown how a cartel HMM can be extended to match a modern competition policy environment. Such a model allows a counterfactual analysis of different competition policy regimes, meaning that it is a potential tool for competition authorities and those wishing to evaluate competition policy.

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Tables and Figures

Table 1: Observed transitions

Industries with a registered cartel (N=109)				
	n_t	c_t	u_t	Row total
$n_{(t-1)}$	207	65	89	361
	(57.34)	(18.01)	(24.65)	(100)
$c_{(t-1)}$	78	312	184	574
	(13.59)	(54.36)	(32.06)	(100)
$u_{(t-1)}$	80	186	3050	3316
	(2.41)	(5.61)	(91.98)	100
Column total	365	563	3323	4251
	(8.59)	(13.24)	(78.17)	(100)
All industries (N=234)				
	n_t	c_t	u_t	Row total
$n_{(t-1)}$	207	65	89	361
	(57.3)	(18.0)	(24.7)	(100)
$c_{(t-1)}$	78	312	184	574
	(13.6)	(54.4)	(32.1)	(100)
$u_{(t-1)}$	80	186	7925	8191
	(1.0)	(2.3)	(96.8)	(100)
Column total	365	563	8198	9126
	(4.0)	(6.2)	(89.8)	(100)

NOTES: Reported numbers are the number of observations and percentage (%) of observations on the row.

Table 2: Descriptive statistics

Variable	#Obs	Mean	S.D.	Min.	Max.
HP – trend	9360	7.22	3.09	2.79	13.17
GDP – neg	9360	6.30	9.91	0	38.89
GDP – pos	9360	6.24	11.23	0	42.43
Total exports	9360	659.75	371.59	179.01	1225.41
Total imports	9360	691.14	375.86	165.81	1256.06
GVP	9216	2809.56	3002.39	4.41	12600
Plants	9216	452.52	376.06	6	1602
Hours/GVP	9216	0.021	0.017	0	0.172
Materialshare	9216	0.573	0.137	0.122	0.919
Death – stock	9360	153.75	172.33	0	581
Death – flow	9360	14.53	14.02	0	47
Birth – stock	9360	423.23	320.76	0	900
Birth – flow	9360	22.50	16.38	0	72

NOTES: The number of observations is lower for the industry variables than others due to missing observations. Total exports and imports and GVP are in million EUROs.

Table 3: Estimation results for H and κ

	H			κ		
	M1	M2	M3	M1	M2	M3
HP – trend	-2.779***	-3.001***	-4.697***	-0.052	0.059	0.141
	(0.5781)	(0.5824)	(0.8796)	(0.3629)	(0.3734)	(0.5776)
(HP – trend)^2	0.364***	0.392***	0.573***	0.072	0.053	0.052
	(0.0728)	(0.0735)	(0.1197)	(0.0501)	(0.0517)	(0.1024)
(HP – trend)^3	-0.014***	-0.015***	-0.021***	-0.004*	-0.003	-0.003
	(0.0028)	(0.0029)	(0.0048)	(0.0022)	(0.0022)	(0.0046)
GDP – neg	0.007*	0.008*	0.026***	-0.012**	-0.012***	-0.014*
	(0.0042)	(0.0042)	(0.0070)	(0.0054)	(0.0055)	(0.0073)
GDP – pos	0.014***	0.015***	0.003	0.031***	0.030***	0.032***
	(0.0042)	(0.0044)	(0.0056)	(0.0046)	(0.0047)	(0.0067)
GVP		-1.69e-05	-2.93e-05		3.57e-05	4.17e-05
		(2.23e-05)	(2.28e-05)		(2.72e-05)	(2.75e-05)
Plants		-0.00011	-0.00011		0.0001	0.0001
		(0.00014)	(0.00014)		(0.0001)	(0.0001)
Hours/GVP		0.502	0.735		-7.130**	-6.338*
		(4.2134)	(4.2969)		(3.5859)	(3.6031)
Materialshare		0.759	1.105**		-1.333***	-1.390***
		(0.5344)	(0.5496)		(0.4271)	(0.4380)
Total exports			-0.004***			-0.001
			(0.0010)			(0.0015)
Total imports			0.005***			0.0004
			(0.0012)			(0.0016)
Constant	7.419***	7.600***	11.418***	-2.756***	-2.092***	-2.269*
	(1.3632)	(1.3666)	(2.0514)	(0.7947)	(0.8393)	(1.2442)
Predictions H, κ	0.926	0.925	0.899	0.231	0.227	0.235

NOTES: Reported numbers are coefficients and standard errors (s.e.). ***,**, and * denote statistical significance at the 1, 5 and 10% level. Reported predictions are the industry-year means of the estimated values.

Table 4: Estimation results for β^c and β^n and the initial probability (τ^n)

	β^c - Birth			β^n - Death		
	M1	M2	M3	M1	M2	M3
$\text{Flow}_{(t-1)}$	0.001	0.001	0.002	0.018***	0.018***	0.019***
	(0.0028)	(0.0028)	(0.0030)	(0.0081)	(0.0081)	(0.0080)
$\text{Stock}_{(t-1)}$	-0.009***	-0.009***	-0.010***	-0.011***	-0.011***	-0.011***
	(0.0007)	(0.0007)	(0.0008)	(0.0043)	(0.0044)	(0.0041)
$(\text{Stock}_{(t-1)})^2$	0.001***	0.001***	0.001***	0.023***	0.023***	0.022***
	(0.0001)	(0.0001)	(0.0001)	(0.0038)	(0.0038)	(0.0035)
Constant	1.845***	1.836***	2.081***	-2.192***	-2.190***	-2.189***
	(0.1867)	(0.1839)	(0.2354)	(0.0599)	(0.0600)	(0.0598)
	M1	M2	M3			
τ^n : Constant	1.659***	1.667***	1.670***			
	(0.1418)	(0.1414)	(0.1412)			
LL	-2582.75	-2560.11	-2550.78			
N	9360	9216	9216			

NOTES: Reported numbers are coefficients and standard errors (s.e.). ***,**, and * denote statistical significance at the 1, 5 and 10% level. The squared birth/death stock variables are scaled by 1/100.

Figure 1: The timeline and our definition of cartel status

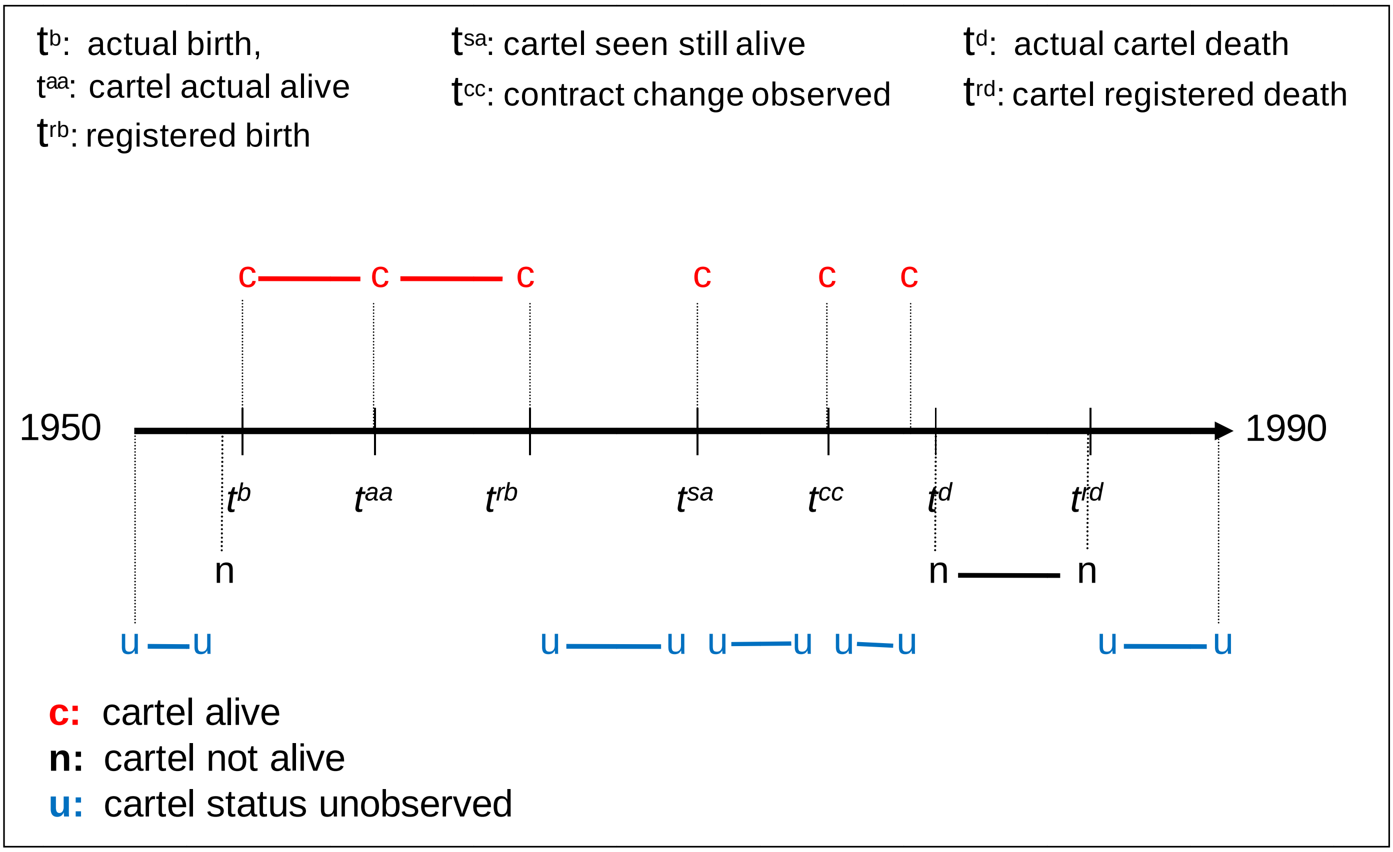


Figure 2: The time variation in H, κ, β_c and β_n

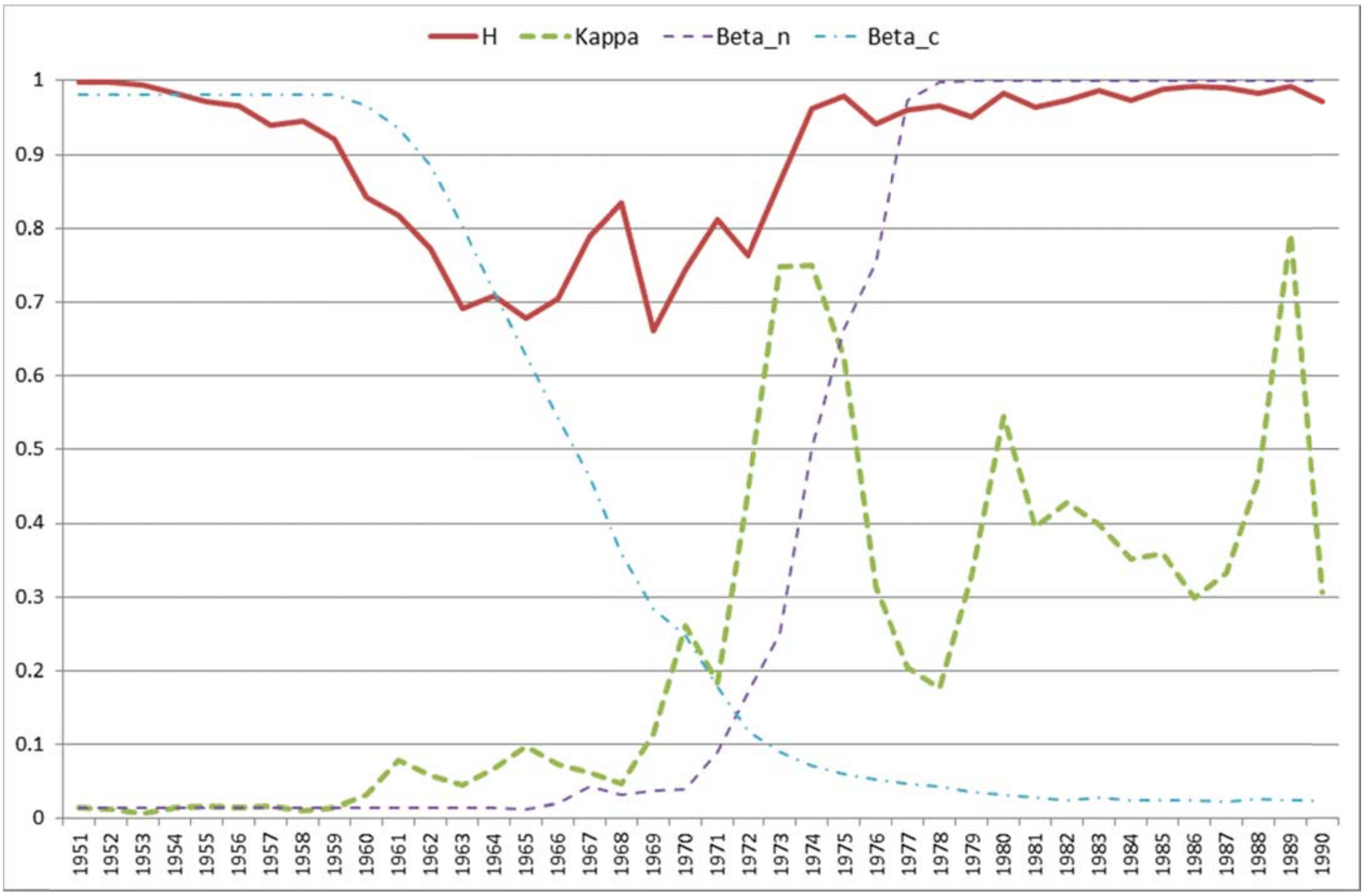


Figure 3: Cross-industry means for the probability of being in a cartel 1951-1990

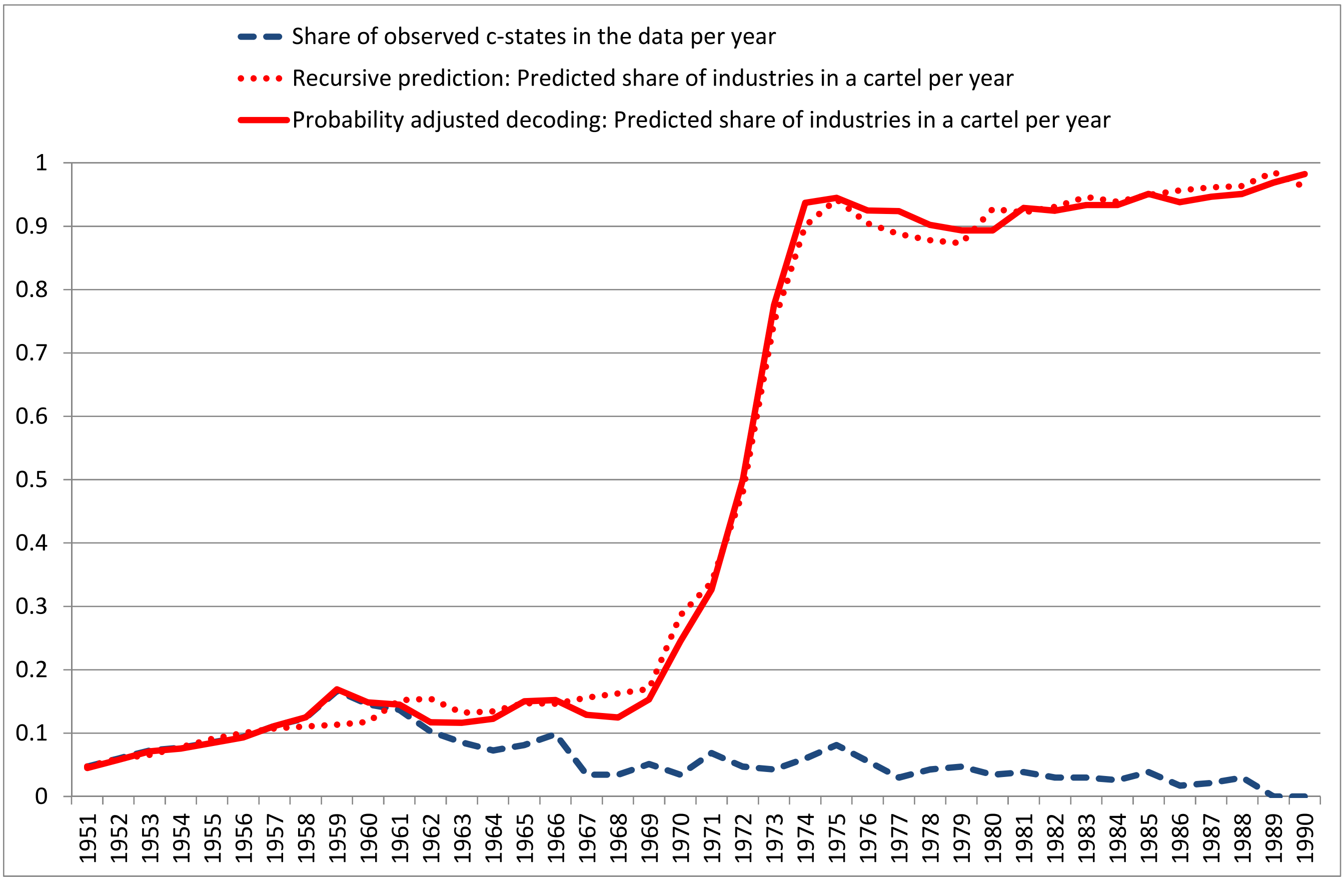
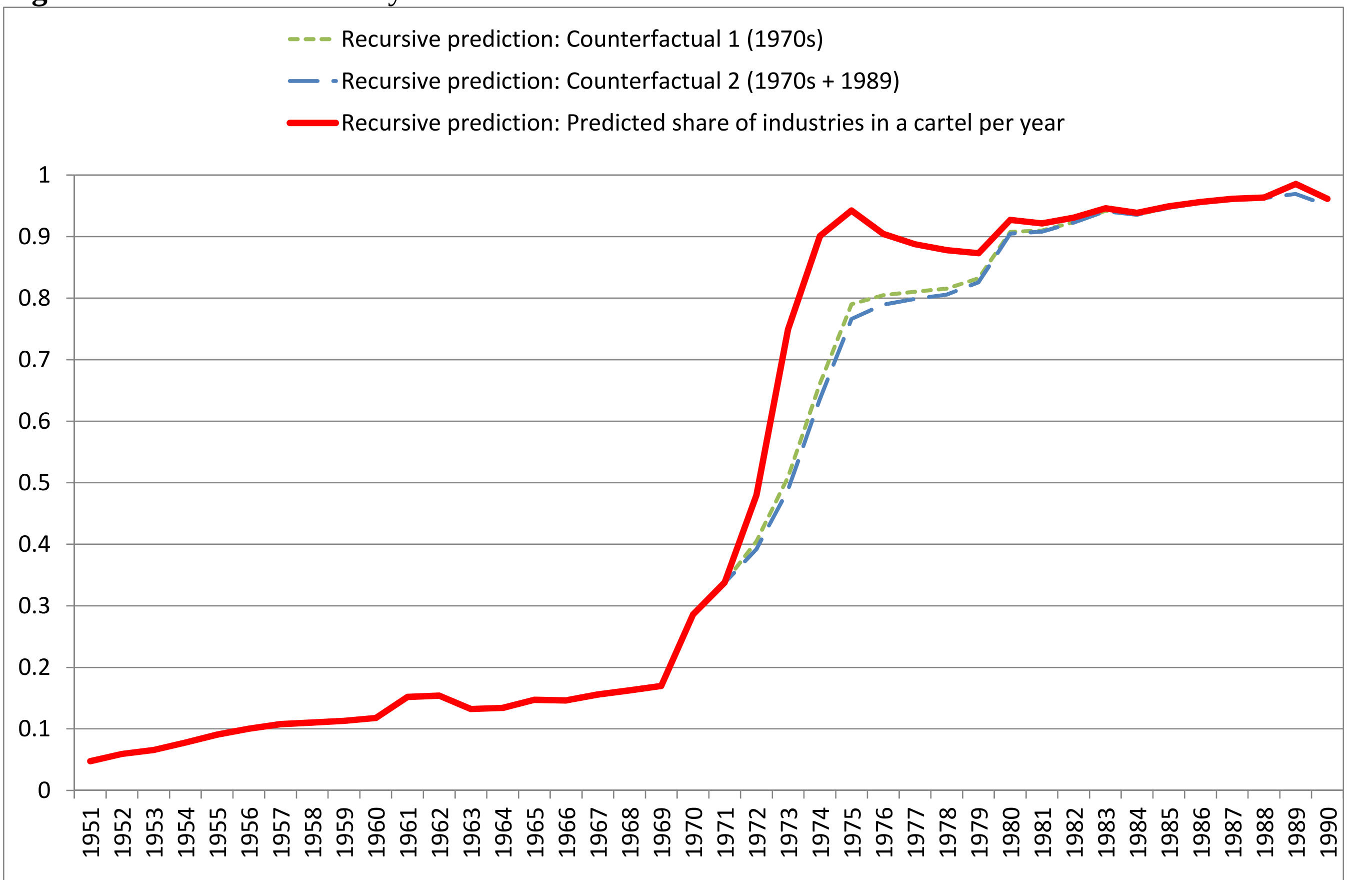


Figure 4: Counterfactual analysis with different GDP shock scenarios



APPENDICES

Appendix A: Finite HMM

To provide a formal definition for a HMM, let us assume that observations are recorded at equally spaced integer times $t = 1, 2, ..., T_i$ for cross-sectional units $i = 1, ..., N$. The observed data for i follow a HMM if the hidden states, $\{Z_{it}\}_{t=1}^{T_i}$, follow a Markov chain and if given Z_{it}, observation O_{it} at time t for unit i is independent of $O_{1t}, ..., O_{i,t-1}, O_{i,t+1}, ..., O_{iT_i}$ and $Z_{1t}, ..., Z_{i,t-1}, Z_{i,t+1}, ..., Z_{iT_i}$. This property means that in a standard HMM, the observations are independent conditional on the sequence of hidden states.

The general econometric/statistical theory and scope of applications of the HMMs is broad (see, e.g., Cappé, Moulines and Rydén 2005, Zucchini and MacDonald 2009, on which this section builds), but for the purposes of our analysis, we can focus on the case in which Z_{it} takes on values from a finite set (state space), $S_Z = \{s_1, s_2, ..., s_{\bar{Z}}\}$, where $\bar{Z}$ is known. We also assume that O_{it} is a discrete (categorical) random variable, taking on values from a finite (observation) set, $S_O = \{o_1, o_2, ..., o_{\bar{O}}\}$, where $\bar{O}$ is known. We define $\mathbf{O}_i$ to be the T_i -dimensional vector of observations on i and $\mathbf{O}$ the $\sum_{i=1}^{N} T_i$ -dimensional vector of all observations. The vectors of hidden states, $\mathbf{Z}_i$ and $\mathbf{Z}$, are defined similarly. Finally, we let $\mathbf{x}_{it}$ denote the K-dimensional vector of covariate values of unit i at t, with $\mathbf{x}_i = \{\mathbf{x}_{i1}, ..., \mathbf{x}_{iT_i}\}$.

The HMM is fully specified by the initial and transition probabilities of the hidden Markov chain and by the distribution of O_{it}, given Z_{it}. For a cross-sectional unit i, these three stochastic elements can be specified as follows:

First, the probability that unit i is at the unobserved state $k \in S_Z$ in the initial period (i.e., $Z_{i1} = k$), given its contemporary covariate values. These initial state probabilities are denoted

$$\tau_i^k = P\left(Z_{i1} = k \left| \mathbf{x}_{i1} \right.\right).$$

Second, the (hidden) transition probabilities give the probability that unit i is at state $k \in S_Z$ in period t, given that it was at state $j \in S_Z$ in period $t-1$, and given its covariate values. These transition probabilities are

$$a_{it}^{jk} = P(Z_{it} = k | Z_{i,t-1} = j, \mathbf{x}_{it}).$$

This formulation shows that we allow the Markov chain to be non-homogenous (i.e., the transition probabilities can depend on a time index) and that conditional on $\mathbf{x}_{it}$, the current state depends only on the previous state (the Markov property).

The third stochastic element of the HMM are the observation (state-dependent) probabilities. The observation probabilities give the probability of observing $w \in S_O$ when the unobserved state is $k \in S_Z$ at t, i.e.,

$$b_{it}^{k}(w) = P(O_{it} = w | Z_{it} = k, \mathbf{x}_{it}).$$

This formulation shows that $b_{it}^{k}(w)$ can depend on covariates and that conditional on $\mathbf{x}_{it}$, the observation at time t depends only on the current hidden state and is independent of the previous observations (and states).

To derive the likelihood of the HMM, let Θ denote the model parameters, $\mathbf{D}_{i1}$ the $(\bar{Z} \times 1)$ vector with elements $d_{i1}^{k}(w) = \tau_i^k b_{i1}^{k}(w)$, $\mathbf{D}_{it}$the $(\bar{Z} \times \bar{Z})$ matrix with elements $d_{it}^{jk}(w) = a_{it}^{jk} b_{it}^{k}(w)$ for $t > 1$, and $\mathbf{1}$ the $(\bar{Z} \times 1)$ vector of ones. As shown in e.g. MacDonald and Zucchini (2009, p. 37) and Altman (2007), the likelihood for the whole observed data can be written as

$$L(\Theta; \mathbf{o}) = \prod_{i=1}^{N} \left\{ (\mathbf{D}_{i1})' \left(\prod_{t=2}^{T_i} \mathbf{D}_{it} \right) \mathbf{1} \right\}$$

where $\mathbf{o}$ denotes the data (the realization of $\mathbf{O}$).

Appendix B: State Prediction

We consider three methods that can be used to analyze the hidden states of industry i at various points in time after the HMM has been estimated. The first is a recursive in-sample state prediction. It uses the estimated initial probabilities and the transition matrix to obtain $Pr\left[Z_{it} = k\right]$ for $t = 1, ..., T_i$. The recursion runs as follows: $Pr\left[Z_{i1} = c\right] = (1 - \tau_i^n)$, $Pr\left[Z_{i2} = c\right] = (1 - \tau_i^n) a_{i2}^{cc} + \tau_i^n a_{i2}^{nc}$, and $Pr\left[Z_{it} = c\right] = Pr\left[Z_{i,t-1} = c\right] a_{it}^{cc} + Pr\left[Z_{i,t-1} = n\right] a_{it}^{nc}$ for $t > 2$, where the probabilities refer to the estimates.

The other two methods are local and global decoding. To give a formal description of them, we build on Zucchini and MacDonald (2009) and introduce some new notation. To this end, let $\mathbf{O}_i^{(t)} \equiv (O_{i1}, O_{i2}, ..., O_{it})$ denote observation history of industry i from time 1 to t, with corresponding realization $\mathbf{o}_i^{(t)}$. Similarly, let $\mathbf{O}_i^{(t+1,T)} \equiv (O_{i,t+1}, ..., O_{iT_i})$ denote 'future' from $t+1$ to T_i , with corresponding realization $\mathbf{o}_i^{(t+1,T)}$. We further define $L_{T_i}= (\mathbf{D}_{i1})' \left(\prod_{t=2}^{T_i} \mathbf{D}_{it}\right) \mathbf{1}$. Finally, we need two $(1 \times \overline{Z})$ vectors, called the *forward* and *backward* probability vectors. For $t = 1, ..., T_i$, the former is defined by

$$\zeta_{i,t} \equiv (\mathbf{D}_{i1})' \left(\prod_{s=2}^{t} \mathbf{D}_{is} \right).$$

This vector has property $\zeta_{i,t} = \zeta_{i,t-1} \mathbf{D}_{it}$ and its k^{th} element, $\zeta_{i,t}(k)$, is the joint probability $Pr\left[\mathbf{O}_i^{(t)} = \mathbf{o}_i^{(t)}, Z_{it} = k\right]$.

The vector of backward probabilities is defined by

$$\epsilon_{i,t}{}' \equiv \left(\prod_{s=t+1}^{T_i} \mathbf{D}_{is} \mathbf{1} \right).$$

The j^{th} component of $\epsilon_{i,t}{}'$ is denoted $\epsilon_{i,t}(k)$ and is equal to the conditional probability $Pr\left[\mathbf{O}_i^{(t,T)} = \mathbf{o}_i^{(t,T)} | Z_{it} = k\right]$. It can be shown that $L_{T_i}= \zeta_{i,t}\epsilon_{i,t}= \zeta_{i,T_i}\mathbf{1}$.

In local decoding, the interest is in finding the state that is most likely to have generated the observed data. For industry i and period t, this most probable state, k_{it}^*, is

$$k_{it}^* = argmax_{k=1,\ldots,\bar{Z}} Pr\left[Z_{it} = k \middle| \mathbf{O}_i^{(T)} = \mathbf{o}_i^{(T)}\right]$$

where $Pr\left[Z_{it} = k \middle| \mathbf{O}_i^{(T)} = \mathbf{o}_i^{(T)}\right] = \zeta_{i,t}(k)\epsilon_{i,t}(k)/L_{T_i}$.

Our modification to local decoding is that we use the probability of the most probable state, not the k_{it}^*. Assigning the latter is sensible e.g. in speech recognition. Assigning the former makes more sense in our application. To elaborate, imagine that a resource-constrained CA needs to decide which markets to investigate. Within our framework, it would want to investigate first that market for which the predicted probability of a cartel is highest, then the market with the second highest probability of a cartel, and so on, until resources have been fully allocated. Using the k_{it}^* assignment would assign a c to all markets for which the probability of a cartel is higher than 0.5, and thereby lose information that the CA would want to use in its decision-making.

Global decoding looks for the entire sequence of states, $\mathbf{z}_i^{(T)}$, which maximizes

$$Pr\left[\mathbf{Z}_i^{(T)} = \mathbf{z}_i^{(T)} \middle| \mathbf{O}_i^{(T)} = \mathbf{o}_i^{(T)}\right]$$

where $\mathbf{Z}_i^{(t)}$ and $\mathbf{z}_i^{(t)}$ denote state histories. There is a dynamic programming algorithm, called the Viterbi algorithm, which can be used to find the optimal sequence for industry i.

Appendix C: Data

[Figure C1 – Birth and death flow and stock here]

[Figure C2 – Graph of GDP and trade variables here]

Appendix D: Hypothetical Cartel Data

Table D1 illustrates the type of *observed* data a cartel researcher might have access to. For this hypothetical example, we set $T = 5$ and use the following notation for the observed states: "Not in a cartel" $= n$, "In a cartel" $= c$, "Detected and shut down by the CA" $= d$, "Leniency" $= l$ and "Unknown / unobserved" $= u$.

Table D1: Hypothetical cartel data

time/industry	1	2	3	4	5	6	...	N
$t = 1$	u	u	c	c	u	u	...	u
$t = 2$	u	n	c	c	n	u	...	u
$t = 3$	u	c	d	c	n	u	...	u
$t = 4$	d	d	u	l	u	u	...	u
$t = 5$	u	u	u	u	u	u	...	u

The (hypothetical) data tell us (see column 1), for example, that for industry 1, $\mathbf{o}_1 = (u, u, u, d, u)'$. This industry had a cartel in period $t = 4$ that was detected and shut down by the CA during that period. The records provide no reliable information about its status prior to or after the detection. Industry 2 had a cartel in period $t = 4$ that was detected and shut down by the authorities during that period. The cartel investigations reveal that the cartel had been up and running for one year prior to its detection, and the court established that no cartel existed two years before the detection. However, the records provide no realiable information about the status of the industry for period $t = 1$ or the post-detection period $t = 5$. Industry 3 can be similarly interpreted; it enters the data in a cartel.

For industry 4, the data are informative about one usage of the leniency facility ($t = 4$). The investigations then revealed that the industry was in a cartel for three years prior to a member applying for leniency. Industry 5 might correspond to an industry that was suspected and investigated for having a cartel over a two-year period. The records (e.g., the court decision) show that it eventually turned out that the industry had no cartel.

For the remaining industries (i.e., for $i = 6, ..., N$ in our hypothetical example), the (published) records of the CA or courts provide no realiable information about their status, perhaps because they have never been investigated for having a cartel or perhaps because they were suspected of having one, but the evidence was too weak to result in a published cartel case.

Appendix E: Hidden Process for Illegal Cartels

The Chang and Harrington model

Consider again CH, who model an industry where (identical) firms in an industry each period simultaneously decide whether or not to collude and where collusion can be detected by a CA. The CA is modelled as i) a detection (and prosecution and conviction) probability $\sigma \in [0, 1)$ and ii) penalty $F/(1-\delta)$ paid by each firm if a cartel is exposed. CH assume that $F = \gamma(Y - \alpha\mu)$ where Y is the (scaled) continuation payoff from being in a cartel. Leniency is modeled as follows: Firms have an incentive to apply for leniency only if their cartel breaks down. If just one firm applies for leniency, it pays a fine θF, where $\theta \in (0, 1)$, while other firms pay F. If all firms apply for leniency simultaneously, each firm pays a penalty ωF where $\omega \in (0, 1)$.

The sequence of events is the same in the main text, except that now, if the industry colludes, the cartel may be exposed by the CA; this happens with probability σ. It may also be exposed to the CA if at least one member of a collapsing cartel applies for leniency. In either case, the cartel is shut down and fines are levied. The structural parameters of this extended model are thus μ,

α, η, H_{IC}, κ, δ, σ, θ, ω and F, the first six describing the industry and the last four the prevailing antitrust policy.

CH show that the ICC of an industry takes the form

$$(1-\delta)\pi + \delta[(1-\sigma)Y + \sigma(W-F)] \geq (1-\delta)\eta\pi + \delta[W - \min\{\sigma,\theta\}F], \quad (1)$$

where Y (W) is the scaled continuation payoff from (not) being in a cartel and $F = \gamma(Y - \alpha\mu)$. Both are functions of (all of) the structural parameters. The L.H.S. of the ICC has two parts. The first denotes the current and the second the expected profits earned if there is collusion: In that case, the cartel is not exposed with probability $(1-\sigma)$ and it earns the continuation payoff is Y. With probability σ the cartel is exposed. Then the continuation payoff is W and the expected fine $F = \gamma(Y - \alpha\mu)$. On the R.H.S., the first term are the profits from deviating. Deviating will yield the competitive continuation payoff W, which is the first component of the second R.H.S. term. A deviating firm will apply for leniency if the penalty from doing so is less than the expected penalty from being caught, yielding the last component of the second term on the R.H.S. side (i.e., $\min\{\sigma,\theta\}F$).

The expected payoff to being cartelized is defined by a recursion that can be solved through a fixed point calculation. Using the fixed point with collusion, Y^*, and rearranging (1) shows that the ICC can be rewritten in terms of π:

$$\pi \leq \phi^* \quad (2)$$

where $\phi^* = \frac{1}{(1-\delta)(\eta-1)}[\frac{\delta(1-\sigma)(1-\kappa)(1-\delta)(Y^*-\alpha\mu)}{1-\delta(1-\kappa)} - \delta(\sigma - \min\{\sigma,\theta\}\gamma(Y^* - \alpha\mu)]$ on the R.H.S is a measure of cartel stability.

To complete our specification of the hidden process in the extended model with illegal cartels, we note that the probability that inequality (2) holds for industry i in period t is

$$H_{it} = H_{ICDM}(\phi^*_{it} - \mu_{it}) \quad (3)$$

where $H_{ICDM}(\bullet)$ again refers to the c.d.f. of the demeaned profit shock.

Figures, Appendix C

Figure C1: Registry deaths and births over time

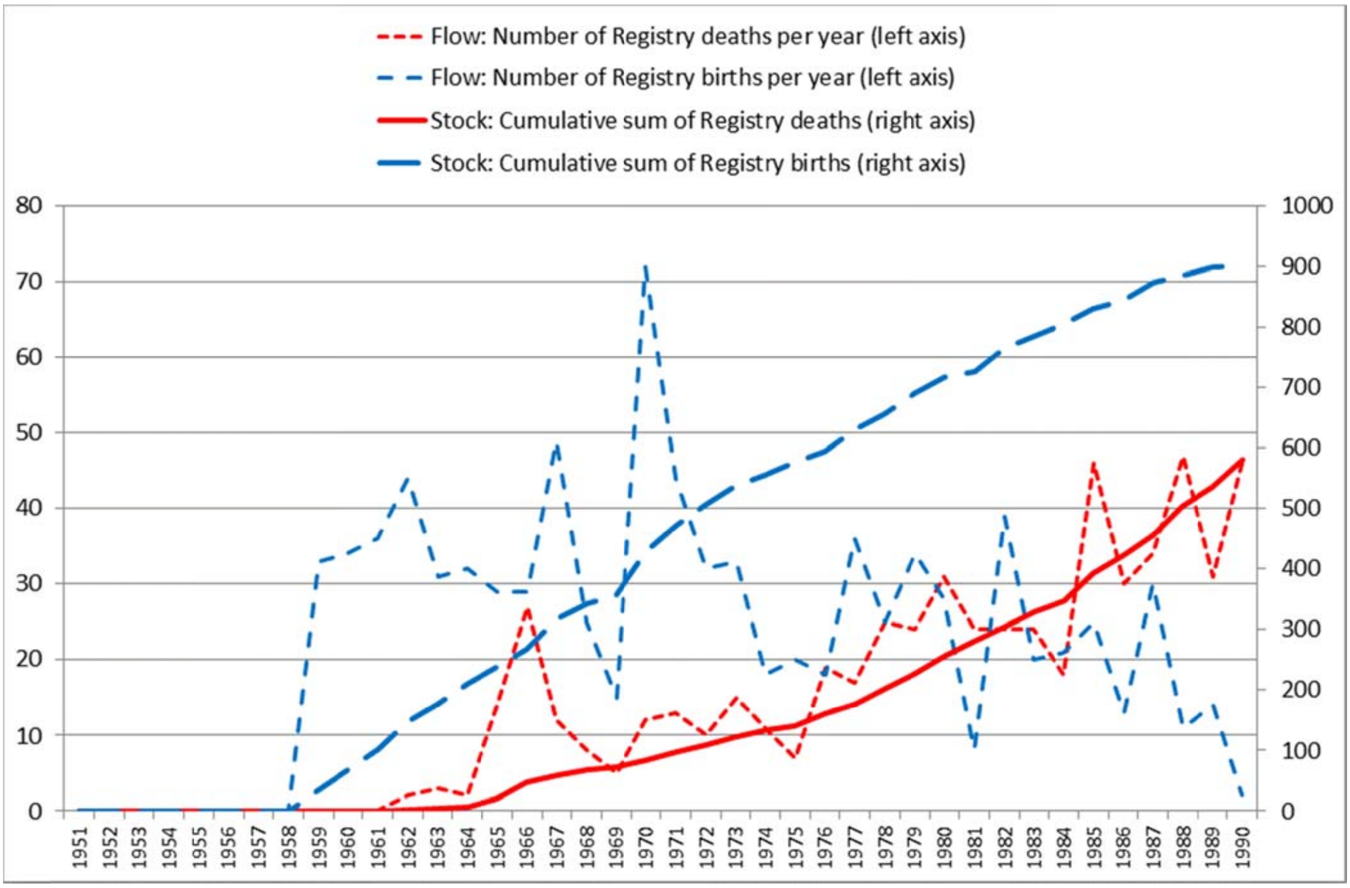


Figure C2: The development in Finnish GDP, long run HP-trend, total imports and total exports