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Toolkit for detecting collusive bidding in public procurement

With examples from Hungary

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ABSTRACT

Toolkit for detecting collusive bidding in public procurement. With examples from Hungary

Across the globe, the exposure of collusive behaviour of companies in procurement markets is predominantly based on qualitative information from firms or individuals involved in collusion. This makes detection rare and titled towards disintegrating bidding rings. Economic analysis, modelling and forecasting have a limited role in this field. However, the increasing availability of large administrative datasets on public procurement transactions and the development of new econometric methods make it possible to develop a wide variety of indicators signalling different forms of collusion.

Based on a synthesis of literature to-date, this paper provides a flexible indicator set deployable as a toolkit across many countries for detecting collusive bidding in public procurement. While no one-size-fits-all approach exists in detecting collusion, robust elementary indicators and analytical tools for adapting them to local contexts can be developed. The paper delivers a conceptual definition and theoretical discussion for each indicator as well as a complex empirical assessment using data on over 75,000 contract awards in Hungary between 2005 and 2012. Indicators are identified, selected, and tested based on relevant academic literature, current best practice policy among competition authorities, court material, and interview evidence from experts and key stakeholders.

Indicators include the relative price of goods and services, skew in the distribution of offer prices, repetition in the pattern of winning companies (i.e. cyclical winning), and co-bidding network constellations suggesting the recurrent submission of losing bids. The proposed toolkit embeds this wide set of collusion risk indicators in a framework which explores theoretically founded co-variation between them and generates benchmarks of ‘normal’ market behaviour using geographical and temporal variation.

The proposed approach differs from previous attempts at generating indicators of collusion in public procurement markets in that it develops a broad ex ante risk-based monitoring framework which is adaptable to a wide range of markets and countries. While it is only an initial synthesis of evidence to date, it serves as a suitable starting point for developing context-specific robust signalling systems.

JEL classification: D72, H57, L12, L13

Keywords: public procurement, collusion, cartel, detection, indicators, Hungary

1 Introduction[5]

Public procurement constitutes a substantial portion of GDP in both high and low income economies. For example, in OECD countries it amounted to over 15% of GDP and 30% of general government spending in 2008 (OECD, 2011). This huge volume of public spending plays a crucial role in economic and social progress if allocated efficiently. However, collusion among firms bidding for public procurement contracts, sometimes supported by politicians and bureaucrats, can inflate prices and lower quality and quantity procured. Collusion among bidding firms constitute one of the biggest obstacles to efficient public spending alongside political corruption and fraud (World Bank, 2009, 2011). As collusion is more likely to arise and operate for a longer period in public procurement than in traditional markets, the need for effective detection methods is great.

Recognising the challenge of collusion in public procurement, virtually every government and development agency has deployed various investigative bodies designed to punish and deter colluding firms. The main methods of identifying various forms of collusion rely on whistleblowers and carry out traditional investigative work using predominantly direct qualitative evidence. This should come as no surprise as courts judging over such cases predominantly rely on direct evidence of collusion (Lianos-Genakos, 2013). However, the efficiency of relying on solely leniency is determined by the market conditions that influence the sustainability and profitability of collusive behaviour. The very nature of public procurement markets – e.g. demand factors increasing potential gains of collusion etc. – significantly hinders the effectiveness of any leniency policy. In addition, detection can be further hampered when collusion in public procurement is associated with corruption which is expected to be frequent due to widespread corruption in public procurement[6] (hivatkozás). Therefore, a new empirical approach is needed for detecting collusive behaviour in public procurement markets.

However, with the rise of 'Big Data', i.e. the real-time availability of large volumes of micro-level electronic data, the avenues for quantitative analysis have greatly expanded. Quantitative indicators can be used in combination with traditional investigative methods to enhance effectiveness and improve detection rates. For example, quantitative indicators can point at specific markets and companies where collusion is more likely. They can be targeted by traditional investigative methods, making better use of limited resources for investigation. While it is very rare across the globe, such a mixed method approach is used by the competition authority in the Republic of Korea (Fair Trade Commission of the Republic of Korea, 2010).

[5] The initial phase of this research was financed by the Hungarian Competition Authority (GVH VKK 2013. contract registration number: AL/638-8/2013, head of research: Tóth, I. J) (Czibik et al, 2014), while the authors relied extensively on their voluntary contributions for realising this study. They would like to express special thanks to colleagues at the Corruption Research Center Budapest working on the Hungarian public procurement database (MakAB) for over four years, especially Kinga Csizmás, Ágnes Czibik, Zoltán Kelemen, and Tamás Uhrin. Furthermore, we would like to thank those who provided insightful feedback on earlier drafts: Zoltán Nagy, Gergely Dobos and Milan Broucek.

[6] In this case the contracting body is also interested in higher returns, and through abuse of administrative tools, the number of involved – hence potential whistle-blower – collusive parties is lower. Both of these factors can significantly reduce the effectiveness of leniency policy.

In spite of relatively few academic and policy innovations in the field, the demand for advanced detection tools is definitely high across the globe. Addressing this unmet demand, this paper strives to

> *provide a flexible indicator set deployable as a toolkit across many countries for detecting collusive bidding in public procurement.*

In order to achieve this objective, this paper does three things: First, it defines and classifies the major types of collusive bidding which provide the backbone of measurement. Second, it develops a set of elementary and complex indicators which are expected to signal collusion in public procurement. Third, it demonstrates how such indicators can be deployed to fit diverse market realities and combined into a coherent framework ready for use by academics and oversight bodies.

This paper makes use of mixed methods bringing together as much relevant evidence as possible. The authors have conducted an extensive review of academic and policy papers discussing collusive bidding in public procurement with particular focus on indicators and evidence of their validity and reliability. In addition, competition authorities' and courts' rich case evidence has been reviewed for implicit indicators revealed by investigators and judges. Finally, an extensive quantitative data analysis of almost 80 000 contract awards and the corresponding tenders in Hungary from 2005 to 2012 has been carried out to explore co-variation among indicators, validity, and reliability. Such a broad evidence-base lends clout to the analysis and points at applicability across the globe. Unsurprisingly, colluding firms behave in markedly similar ways across different regulatory and market contexts.

2 Conceptual approach

2.1 Goals and types of collusive bidding in public procurement

2.1.1 Collusion in public procurement

The characteristics of collusive behaviour[7] in public procurement markets is very similar to that of conventional markets: companies coordinate their behaviour regarding price, quantity, quality or geographical presence in order to increase market prices. The essential long term determinants of the prevalence of this kind of (mis-)conduct are 1) the ability of coordination, 2) internal sustainability (credible punishment system, effective detection of cheating), and 3) external sustainability (ability to exclude new market entrants).

Public procurement markets are more vulnerable to coordinated gaming in light of the above features than traditional markets. In these markets, the outcome is determined by an auction mechanism, implying that there is no quantity adjustment as price changes. Ultimately this leads to an inelastic demand side.

Relatively large contracts in markets where tenders are announced infrequently can incentivize companies to bid aggressively for the first tenders, where they can win lasting

[7] Throughout this paper, the term 'collusion' or collusive ring are used to capture all forms of anti-competitive behaviours as defined above. Other authors in the literature often use by and large overlapping terms such as cartel.

market power. This market power is supported by switching costs (i.e. switching to a new supplier during delivery or in between two related contracts) and the high cost of market entry which is related to economies of scale. These features of procurement markets can further facilitate collusion (Klemperer, 2007). Furthermore, Heimler (2012) argues that in such a ‘winner takes all’ system –with its resistances to quality or quantity adjustments driven by inelasticity of demand – the gains of collusive conduct are higher.

Beyond issues raised by the structure of public procurement markets, one of the most significant problems from the viewpoint of deterring collusion is transparency (Heimler, 2012) which is conducive to government accountability more broadly. Since the results of public procurement tenders are public, the monitoring of the collusive agreements is generally costless, which facilitates the agreement adherence. In the case of procurement markets with many contracts, this monitoring effect is further strengthened, as immediate punishment is possible. Hence detection and the cost of punishment can be significantly lower compared to traditional markets, if tenders are frequent enough.

These characteristics of public procurement markets make the likelihood of creating and maintaining collusion more likely, which is evidenced by the low number of public procurement collusion cases revealed across Europe. The difficulty of detection and punishment call for advanced detection techniques making use of the wealth of data available of bidding and delivery in public procurement.

2.1.2 Types of collusive behaviours

Collusive market behaviour can be categorized according to three dimensions describing the whole spectrum of activities from the implementation of competition restriction to the sharing of rents earned:

1. means of competition distortion or elementary collusion techniques,
2. forms of rent-sharing, and
3. resulting market structure.

When it comes to the means of competition distortion or the so-called elementary collusion techniques, three strategies can be identified which jointly describe the whole universe of available strategies: (i) withheld bids, (ii) non-competitive bidding, and (iii) joint bidding. For the first strategy, one or more companies withhold their bids, so that there is less competitive pressure on the remaining firms, raising the price. For the second strategy, the parties mimic competition. Losing companies either bid a higher price than the competitor(s), their submitted bids are weaker in quality or they simply submit erroneous bids. This is considered to be the most common form of public procurement collusion (OECD, 2014). The third strategy involves companies biding jointly or in a consortium. This is a special form of collusion as it also designates the method of rent allocation among the winning parties[8].

The second dimension of collusion categorization is based on the profit or rent allocation mechanisms used. The most general distinction regarding rent allocation can be based on

[8] Bidding in a consortium is very similar to the case of horizontal mergers, hence the number of competitors decreases, which ultimately can lead to higher consumer prices. Furthermore, this can also be exacerbated by coordinated effects, as information sharing among fewer players becomes easier (Albano et al., 2009). Although, based on a signalling model, a company initiating a consortia would indicate high costs (Estache and Iimi, 2008), economies of scale can also explain such cooperation (Albano et al., 2009).

whether the companies are active or passive members of the public procurement tenders (Pesendorfer, 2000). If they are active, then one of the most trivial profit allocation mechanisms is given by the formation of a consortium. Geographical, market-segmentation or time-based coordinated allocation of tenders also yield straightforward profit allocation mechanisms. When companies are passive, i.e. are not directly present, then a common ownership network (somewhat similar to the presence of consortia) or the use of subcontracts can solve allocation problems. Another straightforward form of redistribution is to simply use informal side-payments, which cannot be examined empirically[9].

The above elementary collusion techniques and rent allocation mechanisms can lead to different market structures reflecting collusion rather than genuine competition. Generally, market distortion can happen by coordinating according to geography, product submarket, or over time, just like rent sharing can follow similar lines. Collusion can result in two types of non-competitive market structures. On the one hand, it is possible that a monopolistic market structure is generated by collusive bidders, hence there is explicit market division with relatively high market shares (see Pesendorfer (2000) or Levenstein (2006)). On the other hand, a competitive market structure can also be imitated by colluding bidders (see Athey et al. (2004), Pesendorfer (2000), World Bank (2011), Mena-Labarthe (2012). In this case, monopolisation can occur by time, as companies agree on a given winning order in a specific market which results in artificially stable market structure. But monopolisation can also happen by geographical or product submarket which implies a more concentrated market only on such narrowly defined markets.

Means of market distortion, rent allocation mechanisms, and the resulting market structures can be combined in a number of different ways each of which is compatible with the logic of rent extraction from collusion. Table 1 succinctly summarizes these three dimensions according to which different collusion types are defined and the theoretically possible combinations of different characteristics. Not every combination is conceptually meaningful and empirically relevant. In addition, the table also depicts which theoretically conceivable characteristic combination, that is collusion type, can be measured using the proposed indicator framework.

Table 1. Main characteristics of collusion types and the availability of indicators

Resulting	Elementary	Form of rent sharing

[9] An important note, that the use of side-payments can lead to a more effective cartel technique, as rents can be maximized, since the most effective firm can serve the market, while in a bid-rigging case, the efficiency losses can be higher (see Pesendorfer, 2000).

market structure	**collusion technique**	Sub-contractor	Consortia/joint ownership	Coordinated bidding[10]	Informal side-payments
Monopolistic market structure	Withheld bids	A			
	Losing bids	B			
	Joint bids		C		
False competitive market structure	Withheld bids	D		F	
	Losing bids	E		G	
	Joint bids				

Notes: every dimension is measured, some dimensions are measured, conceptually non-existent type

2.2 Measurement approach

The proposed measurement approach is highly ambitious as it aims at generating a generally applicable toolkit relevant across time periods, markets, and regulatory regimes. This approach is expected to be fruitful because most collusive bidders are understood as being essentially similar in their goals and strategies on the micro-level, in line with the previous section's discussion.

Public procurement covers practically the whole spectrum of economic activity from the construction of nuclear power plants to the provision of school meals in all sorts of local and global economic environments. The authors cannot hope to understand the detailed complexity of all cases. Instead quantitative data analysis should be deployed to define 'healthy' and collusive public procurement competition across a range of dimensions including prices or number of bidders. Any quantitative claim should naturally be further investigated and eventually verified by investigators knowledgeable of the given market as part of a mixed methods approach. Nevertheless, as such investigations and verifications are part of the traditional methods employed by competition authorities the subsequent discussion focuses on quantitative indicators and the procedures for developing them.

No silver bullet is offered in this paper, rather a five-step fine-tuned process is described, leading to an appropriate measurement framework fit for the local context.

1. **Market definition**: Colluding firms typically target markets as defined by product, geography, and time. Hence, any collusion detection framework has to reliably

[10] While coordinated bidding typically creates a concentrated market structure on sub-markets, taking markets as defined by 'normal' competitive environments as the unit of analysis only allows for false competition to arise rather than monopoly. Hence, the theoretical impossibility of coordinated bidding and monopolistic market structure.

identify markets for indicator development. There are no universally applicable and stable market definitions, rather key dimensions of market differentiation can and should be used for defining alternative market definitions each of which can be used as testing the robustness of risk scores.

2. **Elementary indicators**: A broad set of elementary collusion risk indicators is defined covering as many types of collusive behaviours as possible (Table 1). These indicators are expected to signal collusive bidding, albeit they may well be associated with confounding factors. For example, monopolistic market structure may be the result of markets divided up between colluding firms just as well as severe economic contraction bankrupting all but one competitor on a market. The literature has proposed many elementary indicators, many of which in turn have already been deployed in specific circumstances. Here, only those which can be calculated on widely available public procurement datasets are discussed.
3. **Benchmarks**: public procurement markets and the proposed elementary collusion indicators vary a great deal due to diverse reasons entirely unrelated to collusive bidding; for example, economic growth or regulatory framework idiosyncrasies. In order to identify those values of elementary collusion indicators which are more likely to indicate collusion, ‘healthy’ and collusive markets have to be compared. Ideally, collusive markets are defined using court judgements. In the absence of such judgements quantitative comparisons have to be carried out for elementary indicators. Simple or complex comparisons can exploit exogenous variation in terms of time, geography, or sub-market. For example, the same product market may behave similarly across major regions, but starting from a given time point one of the geographical markets may deviate from the others. While any such ‘deviance from the established norm’ may also be due to a range of alternative explanations, it is the first and necessary step in identifying collusion risks. In order to identify suitable benchmarks, standard tests of statistical significance are clearly insufficient. They must be supplemented with standards of ‘substantial’ size of deviation. What constitutes ‘substantial’ depends on the overall variation on the markets in question.
4. **Indicator co-variation:** When individual indicators suggest high collusion risks, alternative explanations for any such inferences have to be ruled out or at least partially ruled out. To this end, multiple elementary indicators have to be observed on the same market and period with the expectation that they tell a coherent story in line with the theoretical models of collusion types. This implies that some elementary indicators are expected to co-vary. For example in markets where monopolistic market structure has arisen, prices should go up and previously active competitors should abstain from the market. At the same time, elementary collusion risk indicators which signal a different type of collusive behaviour could move in the opposite direction or appear completely unrelated. For example, when the risk of monopolistic market distortion is high, indicators of fake competition should be low. At the heart of the measurement framework is this co-variation between elementary indicators which serves as multiple conditions for establishing collusion risks.
5. **Collusion risk scores**: Assigning categorical or continuous collusion risk scores directly follows from the four prior steps. Markets where elementary collusion risk indicators either don’t surpass pre-set benchmarks or behave in an inconsistent manner receive zero risk score or get assigned a no risk category. Markets where elementary collusion risk indicators surpass benchmarks and paint a picture

consistent with collusive behaviour receive a risk score between 0 and 1 or get assigned a risky category. The strength of this approach is that the use of contract-level public procurement data permits the identification of high collusion risk markets, bidding firms, procuring authorities (if they are implied), as well as contracts. Any of these observation units can display collusion risks over a certain period of time.

In spite of the wide range of elementary risk indicators and innovative ways of combining them, no such approach can hope to indicate the presence of collusion with high precision, hence the reference to collusion risks rather than collusion *per se*. In addition, sophisticated collusive rings can learn the specificities of the measurement methodology and develop strategies to avoid detection. This necessitates a dynamic monitoring framework where emergent forms of collusion in public procurement are incorporated in the detection framework on a continuous basis.

3 Hungarian public procurement data

The database was created from Hungarian public procurement announcements of 2009-2012 (henceforth referred to as PP). The data represent a complete database of all public procurement procedures conducted under Hungarian Public Procurement Law. PP contains variables appearing in 1) calls for tenders, 2) contract award notices, 3) contract modification notices, 4) contract completion announcements, and 5) administrative corrections notices. As not all of these kinds of announcements appear for each procedure, there is missing data in PP for some observations. For example, the type of procedure used determines whether a call for tender is published or not, implying that the variables deriving from the call for tender are missing. Nevertheless, contract award announcements are mandatory in every tender, hence PP has data from contract awards consistently.

The place of publication of these documents is the Public Procurement Bulletin which appears on a weekly basis and is accessible online[11.] As there is no readily available database, we used a crawler algorithm to capture every announcement publicly available. Then, applying a complex automatic and manual text mining strategy, we created a structured database which contains variables with clear meaning and well-defined categories. As the original texts available online contain a range of errors, inconsistencies, and omissions, we applied several correction measures to arrive at a database of sufficient quality for scientific research. For a full description of database development, see Fazekas & Tóth (2012a) and Csizmás, K., Fazekas, M. & Tóth, I. J. (2014) in Hungarian and in somewhat less detail Fazekas & Tóth (2012b) in English.

A major limitation of our database is that it only contains information on public procurement procedures under the Hungarian Public Procurement Law as there is no central depository of other contracts. The law defines the minimum estimated contract value for its application depending on the type of announcing body and the kind of products or services to be procured (for example, from 1 January 2012, classical issuers have to follow the national regulations if they procure services for more than 8 million HUF or 27 thousand EUR). By implication, PP is a biased sample of total Hungarian public procurement of the period,

[11] See: http://www.kozbeszerzes.hu/adatbazis/keres/hirdetmeny/ (in Hungarian)

containing only the larger and more heavily regulated cases. This bias makes PP well suited for studying more costly and more high-stakes collusion where coverage is close to complete.

As contract award notices represent the most important part of a procedure's life-cycle and they are published for each procedure under the Hungarian Public Procurement Law, their statistics are shown in While this discussion concentrated on the Hungarian Public Procurement database (PP), similar databases exist in every high and middle income country with data being available in an increasingly standardised form.

Table 2 to give an overview of the database.

Out of the 118,537 awarded contracts announced in the Hungarian Public Procurement Bulletin throughout 2005-2012 only 78,594 were analysed in most calculations due to five distinctive, but sometimes overlapping reasons:[12]

1. Repetitions,
2. Corrections,
3. Unsuccessfulness,
4. Cancellations, and
5. Framework contracts.

First, Hungarian announcements above the EU threshold have to be published both at the Journal of the European Union (TED) and the Hungarian Public Procurement Bulletin. However, the announcements appearing in TED also appear according to a special format in the Hungarian Public Procurement Bulletin. This leads to duplication of announcements with only slightly different information content. Second, those announcements which were later corrected by a full, repeated announcement were also excluded from our sample for most analyses.[13] More work is needed on this aspect as corrections are not referenced in a standardised fashion in many cases. Third, those announcements or parts of announcements which were contract award notices, but awarded no contract were also excluded. Unsuccessfulness or invalidity are explicitly marked in the announcements; however, as there was no name of winner in a great number of announcements, it is unclear if these are actually invalid announcements or data is simply missing. As crucial information is often missing, we did not include these notices. Fourth, cancellations refer to those announcements which were announced as valid and correct, however, subsequently were had to be withdrawn or modified due to court decisions or withdrawal of the winner. Finally, framework contracts are awarded in two stages whereby winning the contract at the first stage only implies he possibility of bidding for contracts within the framework leading to

[12] In fact, we should extend our data with one sample referring to centralised procurement whereby issuers don't procure on their own rather through a centralised body. Unfortunately, we don't yet have detailed data on who bought and how much from this central public procurement body. For the moment, we account for centralised procurement as one other issuer without knowing the details of the flows of goods and services between individual issuers and the central body. Data acquisition is in progress.

[13] As many corrections don't appear completely anew, rather a specific correction is published which explains which parts of the original announcement were wrong and what the correct information is, we imputed the correct data to the corrected announcements. This introduces a slight bias to our sample as correct information appears to be available in our data earlier than it was in fact for the public. As this only concerns 128 contract award announcements, we consider this to be of relatively minor importance (there are additional corrections for other types of announcements which we still need to take into account).

actual work and payments. Hence, contract awards referring to the first stage of framework contracts are excluded in order to avoid double counting contract values.

While this discussion concentrated on the Hungarian Public Procurement database (PP), similar databases exist in every high and middle income country with data being available in an increasingly standardised form[14].

Table 2. Main statistics of the analysed data – contracts

	2005	2006	2007	2008	2009	2010	2011	2012	**Total**
Total number of contracts observed	5413	9455	6888	12696	21130	28630	17443	16882	**118537**
Total number of repeated contracts	0	0	0	3503	6932	5626	995	4786	**21852**
Total number of corrected contracts*	0	0	0	0	4	81	43	0	**128**
Total number of unsuccessful contracts	675	1134	507	1152	2137	3766	1766	1696	**12833**
Total number of cancelled contracts	7	123	101	986	1249	1597	353	183	**4599**
Total number of framework contracts	0	249	501	705	993	687	369	956	**4460**
Total number of non-repeated, correct, valid, non-cancelled, and non-framework contracts	4731	7952	5796	6812	10921	17927	14070	10385	**78594**
Combined value of non-repeated, correct, valid, non-cancelled, and non-framework contracts (million EUR) *	1128	3086	4365	4591	4611	3850	1836	1290	**24757**

** = a 300 HUR/EUR uniform exchange rate was applied for exchanging HUF values.*

[14] For a global initiative on government contracting data standardization see: http://ocds.open-contracting.org

4 Toolkit in action

This section provides empirical demonstration for the implementation of the proposed toolkit using the Hungarian Public Procurement Database described above. While the elementary collusion indicators are discussed in full, the later steps of the approach cannot be covered in full as there are too many combinations and alternatives to fit in this paper. The selected examples serve to show the logic of analysis while being typical cases, hence empirically relevant, on their own.

4.1 Market definition

The collusive behaviour of companies always manifests itself in specific markets. In other words, identifying a collusive ring is inseparably intertwined with defining the market where it operates. This implies for the proposed toolkit that defining markets used as units of analysis has a crucial impact on results. If we draw the boundaries of markets too narrowly or broadly, the existing patterns in procurement contracts that would indicate the presence of a collusive ring could become unnoticeable.

Defining relevant markets from a collusion point of view can happen either in a bottom-up or in a top-down approach. The bottom-up market definition can be drawn by inspecting unusual or anti-competitive patterns at the contract level using risk indicators defined at the contact rather than the market level. Observing which companies' tendering activities are of high risk through this lens and which markets they operate on ultimately leads to an indirect market definition. The top-down market definition follows from theoretical considerations evoking standard demand and supply side factors such as product substitutability or geographical range of suppliers. Markets can be defined by these factors prior to exploring collusion risks which allows for developing indicators defined in the market level directly. As many of our proposed indicators are defined on the market level, we follow this top-down approach below.

Our analytical goal is to define markets that precisely match the scope of an "average collusive ring", because colluding companies can use their market power to increase prices only if all (or many) potential bidders on the market take part in the ring or non-participating ones are deterred or excluded. This implies that those market definitions which maximize the precision of any collusion indicator exactly match the scope of a collusive ring.

By implication, we need to divide the whole public procurement market into several submarkets. However, it is not possible to decide *a priori* which market definition will be the most appropriate for unveiling collusion. Consequently, this section introduces dimensions (variables) that could be used for defining markets and provides a feasible simple partitioning of the procurement market which will be used for the below calculations.

We defined public procurement markets using three dimensions:

- the type of the product or service, which can be defined based on the CPV (Common Procurement Vocabulary)[15] codes in the contract award announcements;

[15] CPV=Common Procurement Vocabulary. For more info see: http://simap.europa.eu/codes-and-nomenclatures/codes-cpv/codes-cpv_en.htm

- the location of the performance of the contract, which can be identified based on the NUTS codes[16] in the contract award announcements; and
- value of the goods and services procured.

CPV codes define products and services in great detail, although with some measurement error. Between 2005 and 2012 3164 different CPV codes appeared in the Hungarian public procurement database (PP). These codes are extremely detailed e.g. carrots, potatoes or soil testing service, so cannot serve as a base of market definitions. This is because a company which delivers carrots is very likely to be able to sell potatoes too. Therefore we aggregated the codes utilising the hierarchical structure of the CPV nomenclature. After carefully examining different options and looking into actual examples, we chose *a priori* the four-digit detail of CPV codes for determining the boundaries of specific markets. On this aggregation level we can find products and services like “Cereals and potatoes”, “Vegetables, fruits and nuts”, “Building demolition and wrecking work and earthmoving work” and “Test drilling and boring work”. In this manner we defined 921 different markets in the database between 2005 and 2012.

This definition could be altered later in the light of the emerging collusion risk indicators and their sensitivity of market definition. However it will cause a problem anyway that in certain cases issuers buy several different products and services at the same time. The chosen 4-digit market definition solves this problem for the most part because related products and services are bought together in general. When this is not the case, we will revert to the CPV code of the main product or service in the contract award announcement.[17]

For defining geographical boundaries of markets we used NUTS codes of the contract performance location in the first place. We assumed *a priori* that national, regional and local level markets may exist side by side in Hungary even in the case of the same product or service. This means that e.g. the school renewal market of a certain settlement could be interpreted as a separate market which is not equivalent to the school renewal market of another settlement. However, in other cases the location of the project does not separate markets from each other because the companies in the market are able to deliver goods or offer services in the whole country. The highway construction market is a good example for this case. We have to determine which markets are country-wide and what geographical size the local markets have.

Without getting lost in the relationship between specific products, services and the geographical market definition, we simply defined those markets as country-wide where location of the project covers several regions *or* the value of the contract exceeds 100 million HUF. Although this threshold limit is rather arbitrary, we assume that above this limit even a small enterprise would consider establishing a production site in a new location to deliver a contract.

Beyond country-wide markets we use two further regional geographic levels. First, we divide the country into NUTS1 statistical regions: Central Hungary, Transdanubia and Great Plain

[16] NUTS=Nomenclature of territorial units for statistics. For more info see: http://epp.eurostat.ec.europa.eu/portal/page/portal/nuts_nomenclature/introduction

[17] The general problem related to the product market delineation (in case of defining the “real” relevant market) is connected to supply-side substitutability

and North Hungary.[18] Second, we also use NUTS3 codes for defining further, local (county) level submarkets. Therefore, in order to find those markets or submarkets that are relevant from a given collusive ring's perspective, we propose a dynamic approach towards market definition. Hence market level indicators have to be analysed by every possible market definition (see Table 3).

Table 3: Dimensions of market definitions used for calculating indicators

Geography \ Product	CPV code, greater than 100 million	CPV code, less than 100 million
Country-wide	Country	
Regional	NUTS 1	NUTS 1
Local	NUTS 3	NUTS 3

Below we present some descriptive statistics of the market definition used for calculating the elementary indicators in the sub-sections of 4.2. (The dark orange filled rectangles of Table3: country-wide, large contracts [above 100 million HUF based on CPV codes], and regional [NUTS1] markets for smaller tenders [below 100 million]). However, when analysing different types of collusive behaviour, we also have to analyse further submarket level changes (see 4.2.).

Using such a NUTS-based division we defined 5 geographical markets – the fifth market is "foreign/missing" which was excluded from the analysis (Table 4).

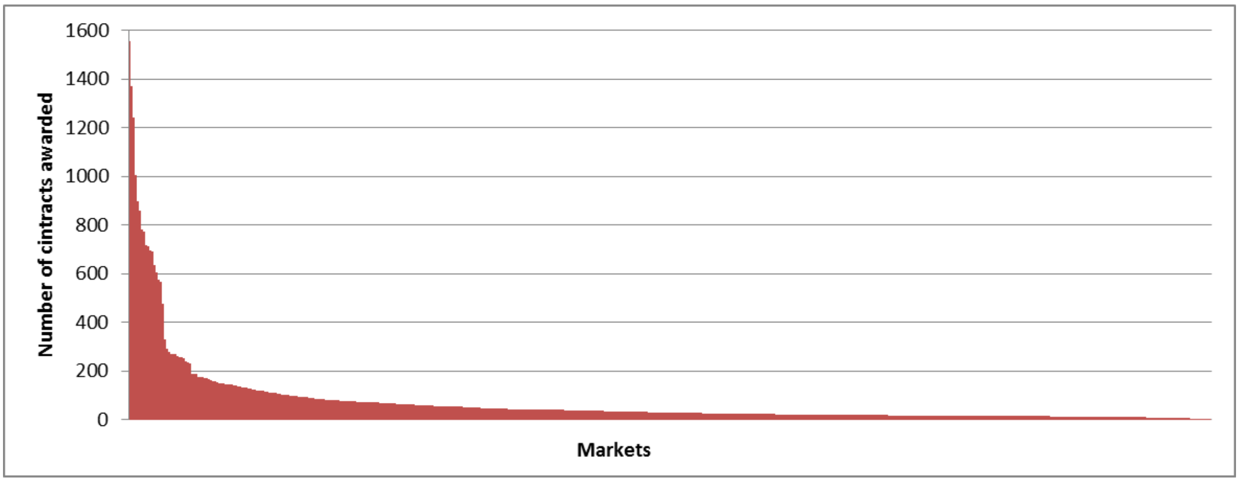
Table 4: Distribution of public procurement contracts by geographical markets, 2005-2010

market	N	Percent
HU1	28,110	35.77
HU2	15,596	19.84
HU3	21,908	27.87
national	21,908	15.24
foreign/missing	1,001	1.27
Total	78,594	100.00

By combining the above defined three dimensions, 2373 different markets could be defined. Most of them are extremely small, with less than 20 contracts awarded in 2005-2012 and less than 3 contracts annually (Figure 1). These markets are far too small for statistical analysis hence they will be excluded thereinafter.

[18] The official contract award announcements indicate the location of the projects with NUTS3 codes, which means counties in Hungary. Using NUTS1 codes in our analysis means some aggregation.

Figure 1. Distribution of markets by the number of contracts awarded, 2005-2012, N=75,737



4.2 Elementary collusion indicators

This section briefly reviews the proposed elementary collusion risk indicators which can be calculated in globally available public procurement databases and have micro-level evidence underpinning their validity in the form of court cases, academic literature, or interviews with practitioners in Hungary[19]. The formula defining each indicator refers to the lowest analytical level, typically a single tender; however, they can be aggregated to characterise companies, markets and periods too. For the sake of brevity aggregation is not discussed in detail.

4.2.1 Categorizing elementary indicators according to collusion types

The below indicators are typically not expected to signal collusion in general, only specific types of collusive behaviour. In order to advance how the elementary indicators co-vary based on the underlying communalities in the collusion type measured, Table 5 groups elementary indicators by the types of collusive behaviour introduced in section 2.1.2. An important note is that in either case (A-G), the indicators depending on the market definition used (see 4.1 and 4.2.1.-4.2.11.), should be calculated for every possible market definition, as the relevant market can vary depending on the form of the collusive ring.

In case A, companies eliminate competition by withholding bids that leads to a concentrated market structure, while rent reallocation happens through the use of subcontracts. Hence we are expecting an increase in market concentration – either on country-wide, regional or local markets (see 4.1.), an increase of missing bidders – consistently with market concentration – and subcontracting.

In case B, companies are faking competition at the tender level by submitting deliberately losing bids. Therefore, the share of faulty bids or the prevalence of superfluous bidders are higher. This conduct can also lead to extremely low range of offer prices and minor difference between first and second offer prices, which is the consequence of coordination.

[19] There are a few indicators that cannot be readily calculated, because the lack of proper data or different public procurement procedures, hence these more complex screens can only be performed by targeted data collection. Such more specialized indicators can be found for example in Kawai and Nakabayashi (2014).

Higher share of subcontracts is indicative regarding the rent reallocation technique used in this type of collusion. This conduct also increases concentration either at country-wide, regional or local market level, depending on the scope and exact rules of the collusive ring.

In case C, prior competitive companies lessen competition by submitting joint bids. This will ultimately lead to a decrease in the number of bids, and a potential increase in market concentration (however, market shares become less accurate, as the real contract allocation is not visible). As forming consortia can often cover all of the previously competitor firms, the range or the difference between the first and second offer price is not always computable. However, if there are other offers – regardless of coordination – range and difference between first and second offers will decrease[20].

In case D, an extremely stable market structure is observed – depending on the scope of the collusive ring. Unlike in case A, rent reallocation is a bit more complicated, as each company wins tenders, but rent sharing is made more flexible through the use of subcontracts too. Hence we expect higher ratio of missing bidders, and an increase in subcontracting as well.

In case E, faking competition happens through involving superfluous losing bidders for the tenders, who submit deliberately losing bids. Therefore we expect extremely stable market structure over time – by the relevant market definition –, while the co-bidding network having many cut-point positions. The losing bids can be measured by either the ratio of faulty bids, or the suspicious distribution of offer prices, measured by the range and the difference between the first and the second offer prices. In this collusive scheme, rent reallocation happens through the use of subcontracting, hence we expect an increase in the prevalence of subcontracting.

In case F, rent reallocation happens through coordinated bidding, which means that tenders are allocated between cartel members through a reciprocal tender allocation. Therefore, tender winning will be dependent on the companies' co-bidding history, which is signalled by the cyclical winning indicator. In this cartel scheme missing bidders can be also observed, as withholding bids can ensure the winning of the predetermined firm.

In case G, the collusive technique used is different from case F, as coordination is done by deliberately loosing or faulty bids instead of withholding offers altogether. That is why besides stable market structure, and cyclical (non-competitive) winning patterns, we expect superfluous bidders with non-competitive offer bids (biased bid price distribution), or high ratio of faulty bids.

[20] If the most efficient companies initiated joint bidding, then offer prices can increase to the level of the less efficient firm's cost levels. Therefore, a significant decrease in the offer price range and difference in the first and second offer price can be observed.

Table 5. Types of collusion and their indicators

Type of collusion	Market structure	Technique	Rent allocation	Market outcome	Market Structure	Collusion technique		Form of rent sharing	Bidding price distribution	
				Indicator 1	Indicator 2	Indicator 3	Indicator 4	Indicator 5	Indicator 6	Indicator 7
A	**Concentrated market structure**	**Withheld bids**	**Sub-Contractor**	Relative contract value	Concentrated market structure	Missing bids		Prevalence of subcontracting		
B	**Concentrated market structure**	**Losing bid**	**Sub-Contractor**	Relative contract value	Concentrated market structure	Superfluous bidders	Ratio of faulty bids	Prevalence of subcontracting	Range of offer prices	Difference between first and second offer
C	**Concentrated market structure**	**Joint bids**	**Consortia**	Relative contract value	Concentrated market structure	Missing bids		Prevalence of consortia	Range of offer prices	Difference between first and second offer
D	**Competitive**	**Withheld bids**	**Sub-contractor**	Relative contract value	Stable market structure	Missing bids		Prevalence of subcontracting		
E	**Competitive**	**Losing bids**	**Sub-contractor**	Relative contract value	Stable market structure	Superfluous bidders	Ratio of faulty bids	Prevalence of subcontracting	Range of offer prices	Difference between first and second offer
F	**Competitive**	**Withheld bids**	**Coordinated bidding**	Relative contract value	Stable market structure	Missing bids		Cyclical winning		
G	**Competitive**	**Losing bids**	**Coordinated bidding**	Relative contract value	Stable market structure	Superfluous bidders	Ratio of faulty bids	Cyclical winning	Range of offer prices	Difference between first and second offer

4.2.2 Relative contract value

Relative contract value is the ratio of the winning bid and the prior estimated price of the tender. As issuers generally expect bid prices go below the prior estimate due to healthy competition, relative contract value can be treated as a proxy for how expensive the contract became; assuming that the prior estimate was non-biased. As the goal of collusion is to generate rents, increased relative contract values can signal collusive behaviour, as ultimately every collusive behaviour results in non-competitive, increased prices.[21] Elevated prices can also result from a range of other factors such as corruption or capacity constraints, however these cannot be readily distinguished.

Increase in relative contract value is a commonly used indication for problems of competition. The general guidelines of OECD (2014) and Oxera (2013) emphasize, that price increases unrelated to cost changes and long term price stability at a higher than average level, can reveal information on market performance. In empirical research, Ishi (2009) defines competitive and cooperative company groups based on relative contract values[22]. Morozov and Podkolzina (2013) investigate whether relative contract values are influenced by factors that are correlated with competition. They find that for tenders with lower (below 90%) relative contract value indicators of competition – for example the number, capacity or experience of the bidders – have significant effects on prices. However, there is no such connection in case of tenders with relatively high (above 90%) relative contract value.

An important question regarding the usability of relative contract value is whether preliminary price estimations can be regarded as a suitable starting point for evaluating the competitive situation of a given market. There are a few types of empirical problems regarding price estimations. First, there is "noise" in the data purely because the announcer does not know the market well enough, therefore their estimation is inaccurate. This kind of bias (be it upward or downward) can be influenced by many dimensions: by sector, tender size, technical complexity, etc. Second, the estimated price can be highly connected to the corruptness of the tender. In case of corruption, the consequent bias can be twofold. On the one hand, the estimation can be excessively low, so that real competitive offers could be circumvented, and the participating parties can increase contract price with an amendment later. On the other hand, unreasonably high estimations can facilitate contract award at an unreasonably high contract value. While these kinds of biases obviously influence relative contract value, only a more complex analysis can address such concerns.

A straightforward indicator for the main outcome of collusion is the relative contract value defined for tender i is the following:[23]

$$RCV_i = winner\ price_i / estimated\ price_i \qquad \text{(i)}$$

where higher RCV indicates higher collusion risks.

This formula of relative contract value is a very general one. Therefore, it can be linked to any kind of collusion setup A-G (see Table 5), hence the outcome of every coordinated

[21] Higher than competitive market prices can result from simply higher prices for the expected quantity and quality, but also from delivering lower quality and/or lower quantity for the same price.

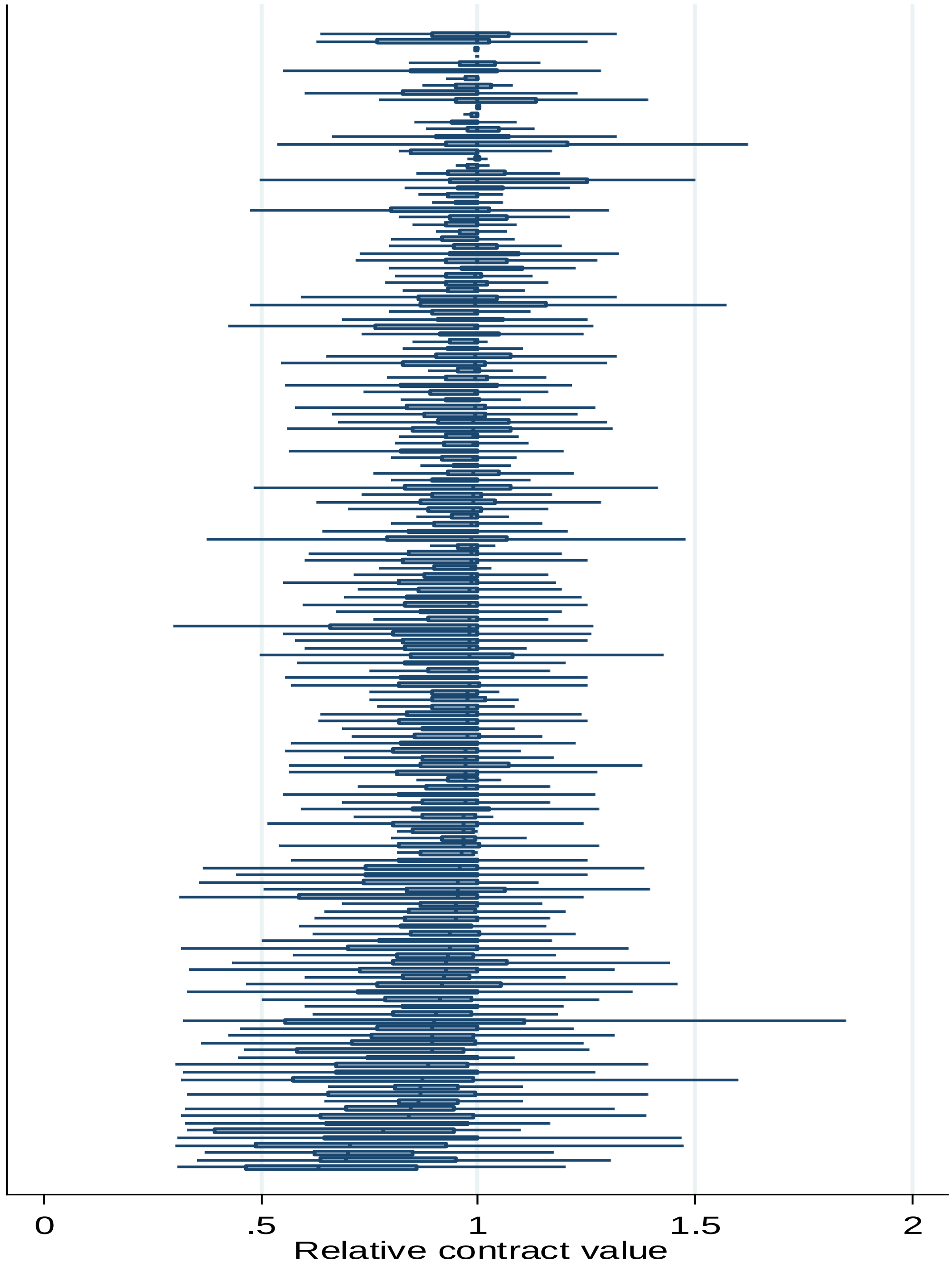
[22] The paper treats tenders above 95% relative contract value as collusive.

[23] Although all the elementary cartel indicators are defined on the level of market, relative contract value is available on the level of tenders allowing for more fine-grained analysis. In the followings we will use *i* for tenders, *m* for markets, *f* for firm and *t* for periods in indicator definitions.

behaviour is ultimately manifested in higher prices. By implication, all the other elementary collusion indicators are expected to be positively related to it (see Table 5).

Figure 2 shows the relative contract value for markets where more than 100 contract were awarded between 2005 and 2012. It can be seen that even markets with many contracts can have significant differences regarding relative contract value. In many cases, the average is very close to 1, or even higher than the estimated price. The bars marking the 25-75% percentiles - that is contracts awarded between the 25th and 75th percentile of relative contract value – further reinforce a picture of large variability within and across markets (variance is large over time too, albeit it cannot be shown here due to space constraints).

Figure 2. Average relative contract value on markets with more than 100 contracts, 2005-2010



4.2.3 Range of offer prices

A key characteristic of public procurement tenders is the distribution of offer prices. Variance, range and skew can each signal a behaviour that is unusual in competitive markets. However, empirical results have mixed conclusions regarding what kind of pattern in offer prices can signal collusive behaviour. For example, Abrantes-Metz et al. (2006) find that collusion leads to decreased variance in prices[24], which is also consistent with the theoretical considerations, as less price variance makes monitoring easier. However, this behaviour might not be useful in public procurement markets, since tenders must be lost in this case. Hence, in case of non-competitive bidding (using artificially high prices) it is important that the 'loosing prices' stay higher than the predetermined winner price.[25] Therefore, for example the skew of offer prices is used as a collusion indicator in Padhi and Mohapatra (2011), and also recommended by Oxera (2013). According to these studies, positive skewness indicates artificially high priced losing bids.

Although detailed bid price statistics are not available in the Hungarian public procurement database (MaKAB), the range of offer prices (that is available) is correlated with their variance. Following the above described implications, both very low and relatively high price ranges can be indicators of non-competitive bidding behaviour – depending on the game played by the collusive parties. Therefore a straightforward indicator for collusion is the range of (relative) bid prices for tender *i*:

$$RBP_i{}^{26} = (highest\ bid_i - lowest\ bid_i)/estimated\ price_i \qquad \text{(ii)}$$

This formula of the range of offer prices cannot serve as a general indicator of collusive behaviour. As a first step for understanding offer price distribution, the connection with the difference between first and second relative offer prices has to be investigated. Furthermore, the co-variation with other indicators of the specified collusion types B, C, E or G (see Table 5) has to be analysed.

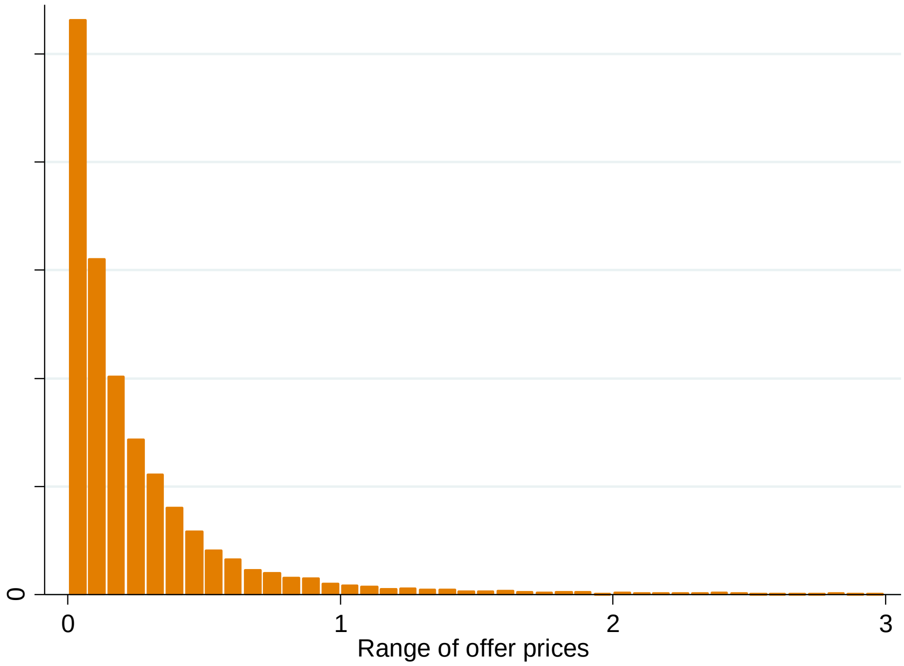
Figure 3 depicts the relative offer price ranges in Hungary between 2005 and 2012 on the level of contracts awarded. It makes it clear that very small price ranges and relatively high price ranges (i.e. those above 0.5) are also prevalent among public procurement tenders.

[24] The investigation of Abrantes-Metz et al. (2006) was not in a public procurement market.

[25] While in case of traditional markets, there is only a quantity alignment, in public procurements there is no continuous transition, hence loosing bids have to be strictly higher than non-loosing bids. Of course, if there is more sophisticated decision making scoring system, the implications for pricing can be altered.

[26] Range of (relative) bid prices.

Figure 3. Distribution of the range of offer prices, 2005-2012



4.2.4 Difference between first and second relative offer prices

In well-established competitive markets where companies regularly bid for similar contracts, offer prices tend to follow a particular random pattern with relatively few outliers. Hence, the distribution of offer prices can be used to gauge collusion risks. Due to the central importance of the first and second best bidders for the outcome of a tendering process, the difference between their offer prices is of particular importance. The difference between the first and second relative offer prices[27] can signal whether the participating companies' pricing strategy is consistent with a competitive market mechanism.

Following Abrantes-Metz et al. (2006), Padhi and Mohapatra (2011) or Oxera (2013), both extremely small and large differences[28] between first and second offer prices can signal collusive behaviour, depending on the internal collusive mechanisms used. Constant (relative) differences over time can further strengthen the probability of coordinated pricing behaviour.[29]

It is important to note, that collusion of only a subset of the firms in a given market can also have detrimental efficiency effects. Therefore analysing the bidding patterns of the first and second offer prices is only an inaccurate attempt to make inferences regarding the whole bid price distribution. For example, through the collusion of the two most efficient firms, the effective competition constraint on pricing will be the marginal cost of only the third lowest cost firm.

[27] Relative means relative to the estimated price, as in the case of relative contract value.
[28] Effective competition under similar cost structures should lead to very similar offer prices, hence this indicator is most applicable to markets with highly competitive companies of similar production technologies.
[29] In the case of competition, the effective cost levels, hence the bid offers of a company should vary over time, hence constant differences between first and second offers are likely artificial.

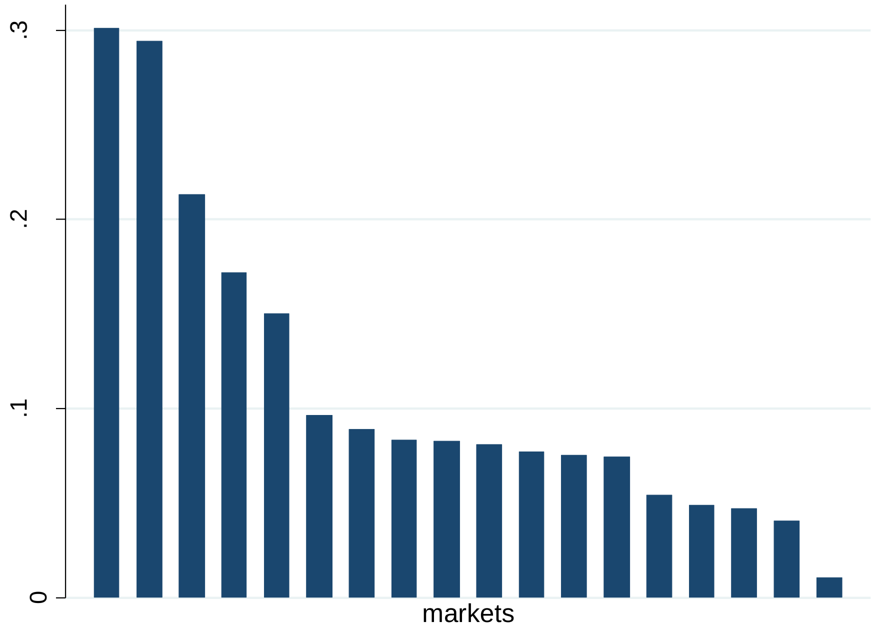
Following the above logic, the difference between first and second relative offer prices (*DbFSOP$_i$*) can be calculated for any tender *i* as the following:

$$DbFSOP_i = RCV_i - RSOCV_i \qquad \text{(iii)}$$

where RCV_i is the relative contract value, whereas $RSOCV_i$ is the ratio of the second offer price and estimated contract value (first and second relative offer prices respectively). The indicator can be used either on the tender level, or for tracking the evolution of the offer price differences over time by market. The difference between first and second offer prices is not a general indicator of collusion risks, hence it has to be complemented with other elementary indicators related to cartel types B, C, E or G for inferences on anti-competitive behaviour (see Table 5).

Figure 4 shows the average difference between first and second relative offer prices in markets with at least three contracts. It can be seen that the difference is volatile, between 1-30 percentage points. Both the extremely low and high average differences can signal anti-competitive bidding.

Figure 4: Difference between first and second relative offer prices[30]



4.2.5 Concentrated market structure

One of the major results of collusive bidding is concentrated market structure instead of a competitive market with multiple players. Concentration in a public procurement market refers to a single or few company winning all the contracts while competing bidders are either entirely absent or only mimic participation. It can be taken as a sign of collusive behaviour if it takes place on an otherwise competitive market. Concentrated market structure can be also closely linked to rent sharing methods. As Pesendorfer (2000) shows, when tender

[30] This Figure is based on a preliminary dataset that contains second offer prices only from 2012, hence it has only 168 observations.

completion is done by the most efficient companies (though not competitively) in order to reap the largest profits possible, market shares can rise. By implication, concentrated market structure should be defined with reference to an elevated market concentration compared to a competitive situation. A clear-cut situation when concentration signals collusion is when a particular market turns from competitive to a concentrated one in a short period of time without any apparent alternative explanation such as changing regulations, technology, or steep decline in total demand.

Concentrated market structure can be defined in two principal ways: 1) market share of the largest company in the market; 2) C4, the combined market share of the four largest companies in a given market; and 3) the Hirschman-Herfindahl Index (HHI). (In each case, we use market shares based on contract value.) The largest' company's market share on market *m* and period *t* is calculated in the following way:

$$MSoLC_{mt} = \text{Total contract value of the largest company of the market}_{imt} / \text{Total value of contracts awarded}_{imt} \qquad \text{(iv)}$$

$C4_{mt}$, the combined market share of the four largest companies in the *m*th market during period *t* can be measured as:

$$C4_{mt} = \sum_{i=1}^{4} S_i \qquad \text{(v)},$$

where S_i is the market share of company *i*. HHI is a broader indicator, taking into account the market shares of all the companies on the market. For market *m* and period *t*, it is defined as the following:

$$HHI_{mt} = \sum_{i=1}^{i=n} S_i^2 \qquad \text{(vi)},$$

where n denotes the total number of companies in the market *i* in period *t*. Both high MSoLC, C4, and HHI indicate high collusion risk.

It is important to note, that concentration indicators have to be calculated using various market definitions (see 4.1.), as certain types of collusive behaviour can be only seen on a submarket level. Therefore, interpreting the indicators of concentrated market structure – calculated for different markets – have to be consistent with other indicators belonging to the same type of collusive scheme.

Concentrated market structure has to be assessed jointly with indicators associated with cartel types A, B or C (see Table 5). Each of the related indicators point to the orchestration of bidding in order to allocate the contract to a pre-selected company and at rent sharing among colluding firms in different ways. Hence, the different combinations of elementary collusion risk indicators suggest different types of collusion beyond reinforcing each other's validity. Given that any of these types are observed, we can expect a positive correlation between the above linked collusion risk indicators. Nevertheless, the lack of association between these indicators can still mean that the particular type of collusion in question is only captured by one of the indicators rather than the combination of them.

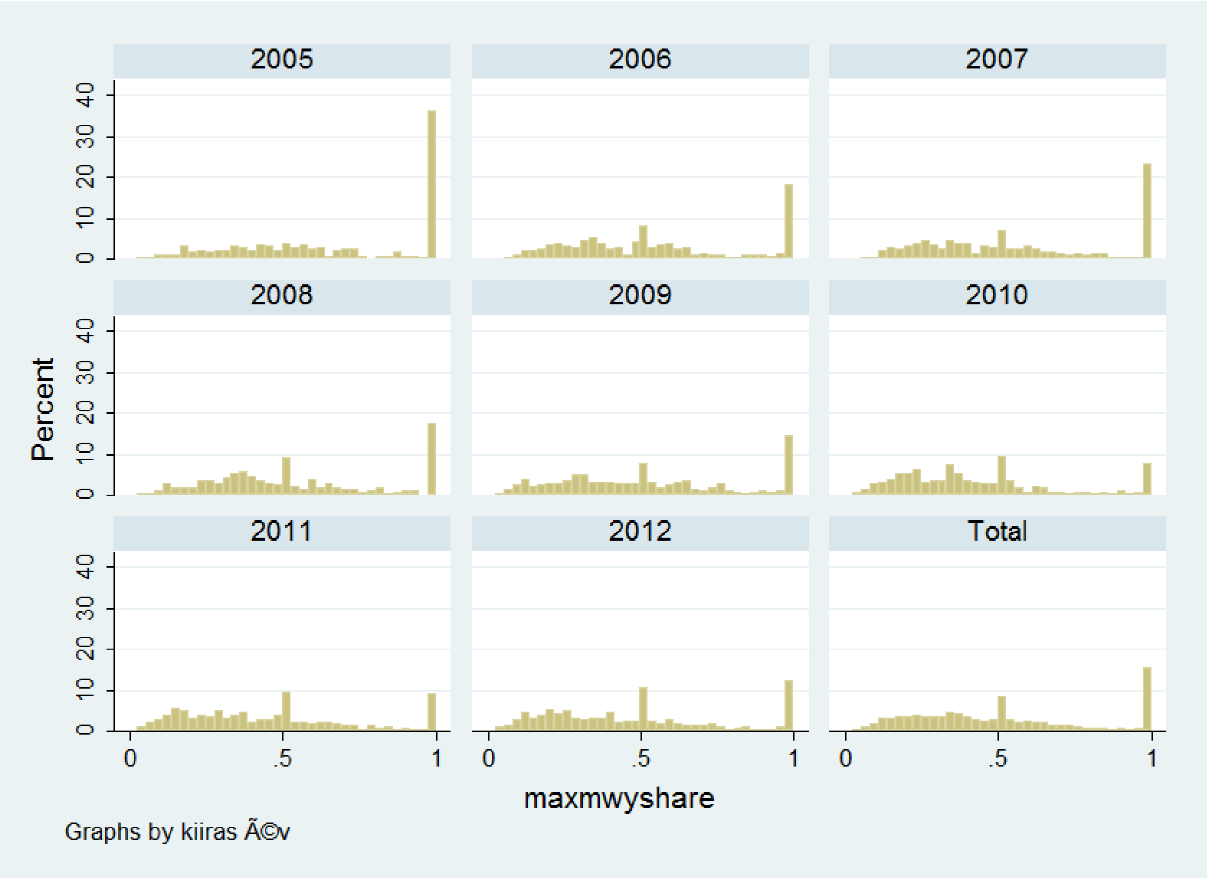
The market share of the largest company on the market is somewhat more suitable indicator to our needs as it can more directly signal the dominance of that member of the collusive ring which extracts the rents in the market. In addition, MSoLC, C4, and HHI are all positively correlated, by implication, only MSoLC is discussed in detail.

Markets vary widely according to their largest' companies' market shares over time as well as within the same year (

Figure 5). Overall, about 15% of markets have only one company winning all the tenders in the calendar year, while this figure can go even higher than 20% in a year. This holds when we consider markets with substantial total activity; that is at least 20 contracts awarded in the observation period.

The substantial temporal variation lends support to the benchmarking exercise later on where the same market is tracked over time. In addition, where such a pattern is simultaneous on markets with companies which used to be competitors, this indicator can prove to be powerful on its own in spite of its simplicity and susceptibility to alternative influencing factors.

Figure 5. Distribution of markets per year according to the market shares of largest companies in the market, markets with at least 20 contract awarded in 2005-2012, N_{total}=3,508



4.2.6 Stable market structure

Stable market structure indicates that there is artificially low variance in market shares on the market, which is not consistent with natural, competitive market outcomes. Atheyand Bagwell (2001) or Atheyet al. (2004) shows that following a market share rule for allocating rent can be also an optimal conduct in collusion[31]. Regarding empirical studies, Pesendorfer (2000) shows that when instead of side-payments the rent reallocating mechanism is bid-rigging, relatively stable market shares can be observed. Mena Labarthe (2012) also shows that in the collusive period, the market shares of the colluding parties were practically the same[32]. In Harrington (2006), two relevant collusion indicators are introduced based on market structure: highly stable market shares over time and highly stable market shares of a subset of firms.[33]

In order to have a consistent framework for interpreting suspicious signs related to market structure, we analyse the same indicators for stable market structure as for concentrated market structure. However, here we examine whether concentration measures are extremely stable over time or not. Following this logic, the proposed indicators of stable market shares are the followings:

$$SMS(MSoLC)_{mt} = \sqrt{E((MSoLC_{mt} - MSoLC_{mt})} \qquad \text{(vii)}$$

$$SMS(C4)_{mt} = \sqrt{E((C4_{mt} - E(C4_{mt})^2)} \qquad \text{(viii)}$$

$$SMS(HHI)_{mt} = \sqrt{E((HHI_{mt} - E(HHI_{mt})^2)} \qquad \text{(ix)}$$

Similarly to the case of concentrated market structure, these indicators also have to be calculated by every market definition (see 4.1.), as certain types of collusive behaviour can be only seen on a submarket level.

Stable market structure have to be assessed jointly with indicators associated with cartel types D, E, F or G (see Table 5). It is important to note, that some collusive schemes can induce a stable market structure on a broader market, but increased concentration at the submarket level. Therefore, the assessment of the two types of indicators related to market structure can be often interrelated.

Figure 6 shows the variance of HHI among different years. It shows that there are markets, where there is only minimal change in market structure, based on this indicator.

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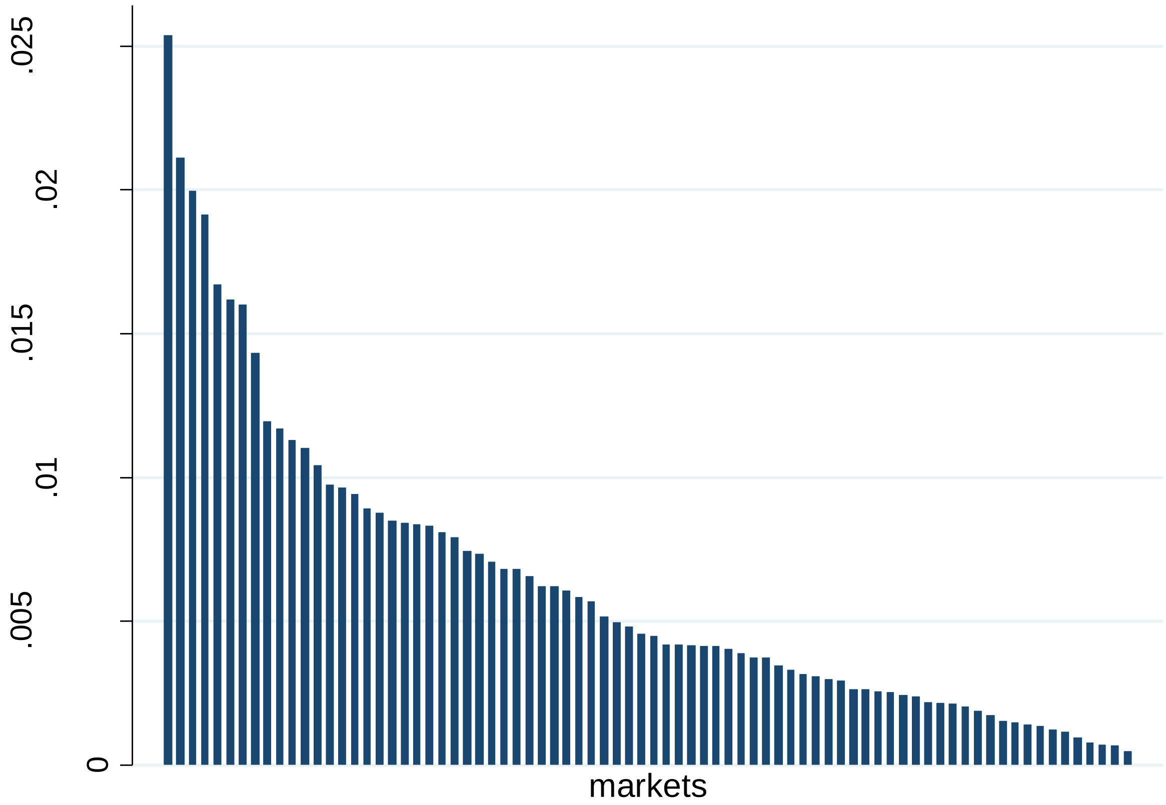
[31] Given plausible assumptions on costs.

[32] In Mena-Labarthe (2012) a Mexican pharmaceutical cartel was investigated.

[33] Also, Harrington (2006) argues that market shares are often fixed at the pre-collusion levels.

Figure 6: Variance of HHI per market among different years



4.2.7 Cyclical winning

Cyclical winning indicates whether winning patterns are consistent with efficient competitive behaviour or rather with coordination, which is unrelated to cost factors.

In the case of competition, winning patterns – or bidding patterns – should be based on the companies' costs. Following this logic, more experienced or bigger companies, those who have excess capacities should have lower bid offers, hence winning a given tender is related to individual firm characteristics. Therefore, one should not expect that the companies' co-bidding history is related to their winning patterns. Consequently, there should be no relation between firms' bidding history at a given market and tender winning.

Inspecting suspicious bidding/winning patterns is a rather simple measure of a potentially anti-competitive bidding scheme, that is also part of the OECD recommendations (OECD, 2014) as an A,B,A,B winning pattern. This concept is formalized in Padhi and Mohapatra (2011), as they suggest that significant partial autocorrelation in the companies' winning patterns can indicate collusion[34].

Based on this simple idea we propose the following straightforward indicator for cyclical winning for firm *f* on market *m*:

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[34] Obviously, autocorrelated winning patterns can be explained by switching costs etc. Therefore, this should be further validated by other indicators as well.

$$CW1_{f,m} = PACF_{f,m} \qquad \text{(x)}$$

Where $PACF_{f,m}$ stands for the partial autocorrelation function of firm *f*s winning[35]. We expect, that companies, whose winning patterns are partially autocorrelated can follow an anticompetitive bidding behaviour. It is important to note, that winning patterns are not independent of market definition, hence partial autocorrelation should be calculated by diverse market definitions (see 4.1).

However, finding significant partial autocorrelation in winning sequences can be coherent with competitive behaviour as well leading to an overestimation of the number of colluding firms. Therefore, as it is showed in Ishii (2009), coordinated bidding behaviour is best identified when firm level characteristics such as capacity constraints are also controlled for. In order to have a market level indicator for cyclical winning (here, we are following the logic of Ishii (2009)) a 'balance' contract values between every two company has to be investigated. In case of collusion, there are deliberately losing bidders, where a kind of 'debt' is generated by the winning company in relation to the loosing ones, that is equal to the contract value. If rent allocation is based on coordinated bidding, then the winning firm – unrelated to its actual costs – has to return this favour to the previously losing ones, by deliberately losing in subsequent tenders. Therefore, the prior loser companies' winning chances will depend on their bidding history in the following period, namely on how many other companies have to return the favour for past loses. Based on this logic a variable can be defined for every firm that indicates the number of other firms that have to return the favour of prior losing – following Ishii (2009), we name it as a "score" variable (s_{fi}).

Therefore – despite the relatively extensive data requirements based on procurement data, and firm level data – the following simplified regression can be estimated:

$$win_{fi} = \alpha s_{fi} + \boldsymbol{\beta}'\boldsymbol{a}_{fi} + \varepsilon_{fi},$$

where *f* refers to a given firm, *i* to a given tender; *win* indicates whether company *f* has won the tender *i*, *s* stands for the value of prior favours to company *i* which has to be returned by the other bidding companies, and ***a*** contains the vector of control variables such as revenue of the given company, or the number of active years in public procurement markets.[36] Following the above logic, we expect the effect of s_{fi} on a company's winning chances to be zero in a competitive case. Therefore, if s_{fi} has a positive effect on winning, then it means that co-bidding history matters, which is only consistent with a collusive bidding behaviour.

Based on this logic, a market based indicator of collusion can be defined as the following:

$$CW2_m = \begin{cases} 1\ if\ tender\ winning\ is\ related\ to\ prior\ bidding\ behavior^{37} \\ 0\ if\ tender\ winning\ depends\ only\ on\ costs \end{cases} \qquad \text{(xi)}$$

Both of the proposed indicators of cyclical winning have to be calculated by multiple market definition, as cyclical winning patterns can affect only sub-markets. Furthermore, cyclical

[35] The partial autocorrelation of a simple dummy variable can be investigated (1: if the given company wins, 0: if not).

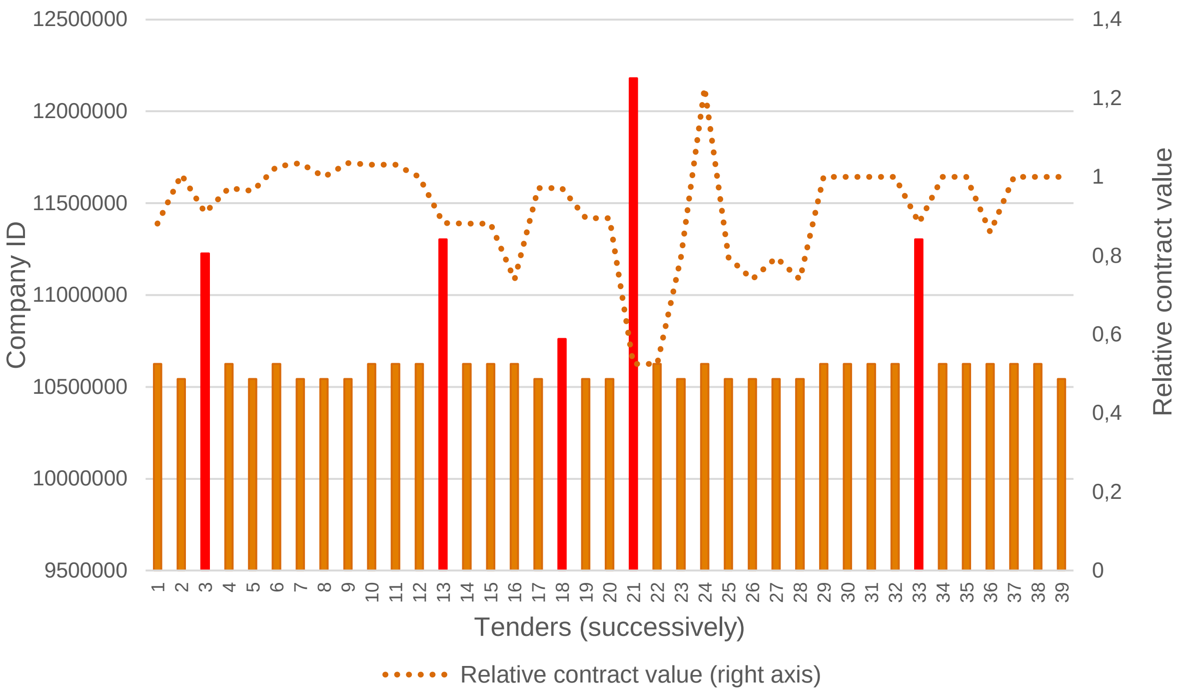
[36] This general model can be further sophisticated – e.g. firm fixed effects or other control variables can be included, or other regression models can be used.

[37] s_{fi} has a significant positive effect on winning.

winning has to be assessed together with indicators related to cartel types F and G (see Table 5).

Figure 7 is an illustrative example, showing a market (diesel oil), where two companies dominate tender winning (dark orange bars). Although this is a restricted sample, it is apparent that if a new company wins the tenders (red bars), the prior increasing relative contract value significantly falls. The indicators of cyclical winning proposed above show these kind of coordinated bidding behaviour statistically.

Figure 7: Tender winning and relative contract value, 2005-2012[38]



4.2.8 Missing bidders

Keeping away from certain tenders is a straightforward way to remove competition, hence missing bids of a previously active company at a given market can indicate collusive bidding. Although there is no empirical research on the collusive schemes using missing bids, as this is a bidding strategy which leads to the same outcome as using faulty or overpriced bids, it should be considered. Furthermore, withdrawing of bids is also mentioned in the OECD (2014) recommendation, as a suspicious phenomenon.

A straightforward indirect indicator of missing bidders is the prevalence of single bidding. Although, it is a rather general indicator that can simultaneously indicate corruption as well (see e.g. Fazekas et al., 2013b), the outcome of a collusive agreement based on withholding bids will also lead to such an outcome. Hence a general indicator of missing bids can be the following for a tender *i*:

[38] This is a restricted sample, as relative contract value is missing in a few cases (either the estimated price or the winning price is missing). However, the market share of the two companies is very similar all in all

$$MB1_i = \begin{cases} 1 \; if \; only \; 1 \; bid \; is \; received \\ 0 \; if \; more \; than \; 1 \; bid \; is \; received \end{cases} \quad \text{(xii)}$$

As this indicator is an oversimplified measure of tenders potentially affected by collusion, a more nuanced approach may be more precise, where we identify markets having diminishing competition through decreasing number of bids complemented by firms with strategic bid retention. Following this logic, we propose three different indicators that can signal collusion through coordinated bid withholding:

$$MB2_{mt} = \frac{Number \; of \; bids_{mt}}{Number \; of \; tenders_{mt}} \quad \text{(xiii)}$$

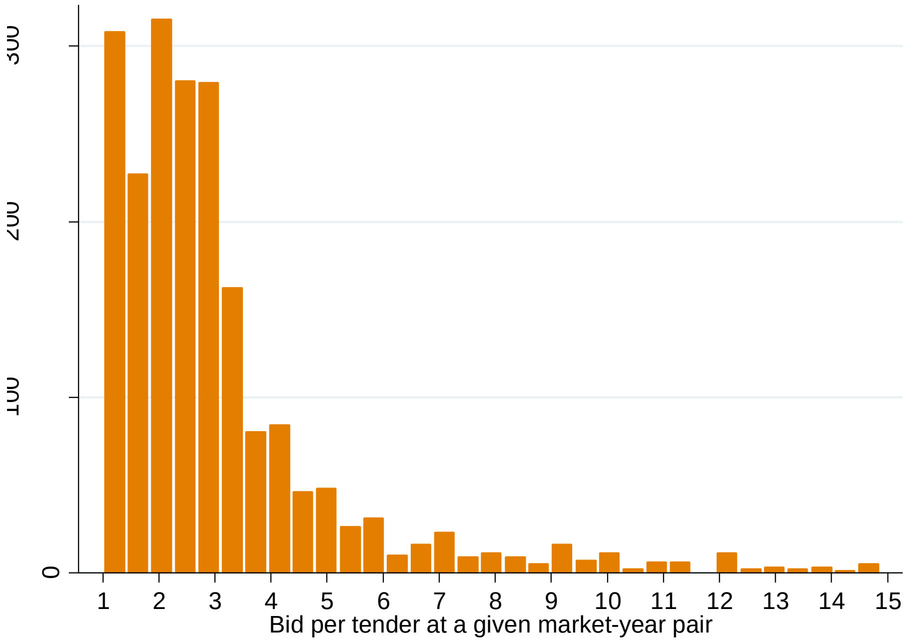
$$MB3_{mt} = \begin{cases} 1 \; if \; companies \; withhold \; bids \; from \; different \; submarkets \; simultaneously \\ 0 \; if \; companies \; bid \; in \end{cases} \quad \text{(xiv)}$$

$$MB4_f = \frac{number \; of \; winning \; bids_{mf}}{number \; of \; offers_{mf}} \quad \text{(xv)}$$

Similarly to other indicators, MB2 and MB3 are not independent from market definition, which is why these have to be calculated by different market definitions. Observing missing bids should be also consistent with other indicators related to cartel types A, C, D or F (see Table 5).

Figure 8 shows the distribution of market-year pairs according to the average number of bids per tender. It is apparent, that in many cases, there are only one bid per tender, and in most of the cases, the number of competing bids do not exceed even three. Sudden year-to-year changes in the average number of competing bids can signal the creation or termination of a cartel which could be validated with other indicators as well.

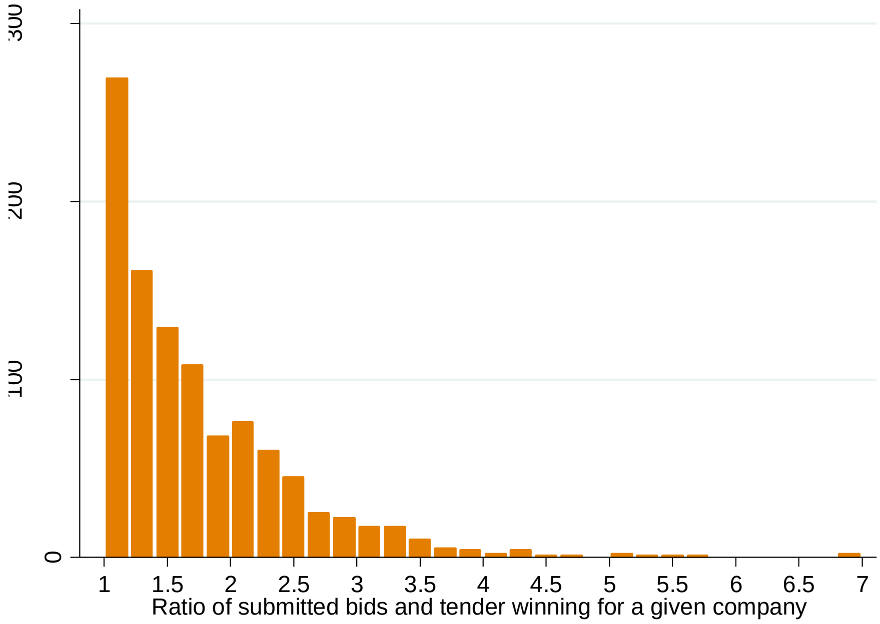
Figure 8: Distribution of market-year pairs according to the average number of bids per tender at a given market-year pair, 2005-2012[39]



[39] The sample is restricted to those tenders, where the maximum of bids were below 100, and the average number of bids per tender is below 15.

Figure 9 shows the distribution of companies according to the average number of bids submitted per winning tender. Although it shows a restricted sample, where only companies with more than 10 winning tenders are included, it is indicative, that there are many cases, when all of the submitted bids of a given company is also a winner bid. However, there are companies, who submit bids frequently, while winning only very rarely. Both kinds of extremes can be indicative on collusive behaviour.

Figure 9. Number of companies according to the ratio of submitted bids and tender winning, 2005-2012 (companies with 10+ tender winning)[40]



4.2.9 Superfluous losing bidders

One of the most straightforward ways to mimic competition while in fact coordinating bidding and pre-determining who wins is when competitors recurrently submit losing bids making a pre-selected company a sure winner. This indicator captures such a situation.

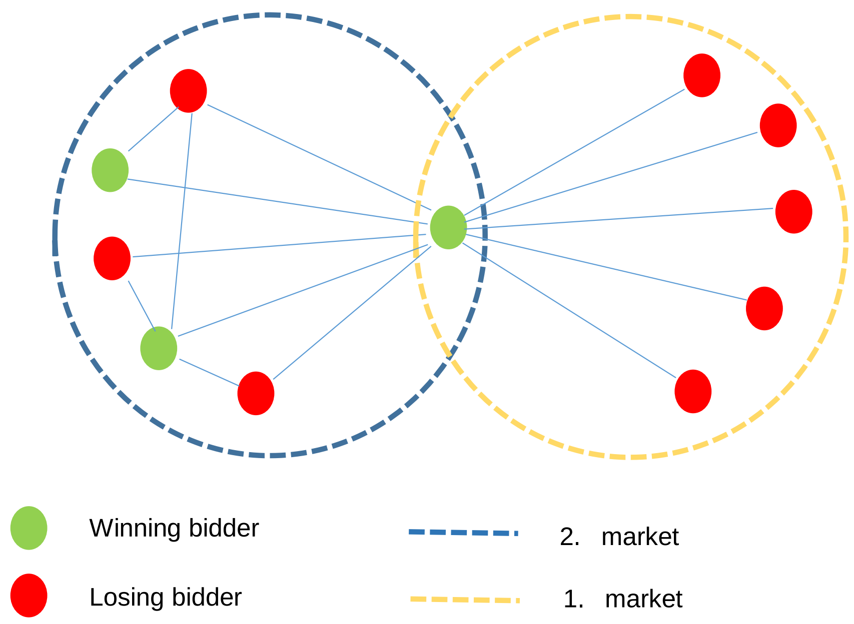
In a truly competitive context more than one company is expected to win over time, while companies losing throughout a prolonged period are unlikely to keep bidding. Thus, observing a dominant company winning always or almost always while a set of 'competitors' bidding, but losing always or almost always may signal collusion. This is distinct from the situation when losing bidders submitting incomplete or erroneous bids which get disqualified as the Hungarian Public Procurement Bulletin only reports the names of bidders which submitted valid bids. Submitting faulty bids is measured by the prevalence of faulty bids (for details see below).

When colluding firms control the entire market and the company extracting rents (i.e. winning) is the same over a longer period, it is possible to identify distinct network formations underlying this kind of collusion. In a co-bidding network, that is a network of bidders where

[40] The sample is restricted, as only those tenders could have been included that were announced in a separate announcement. Hence, the information from tenders that were announced in multiple lots could not been incorporated. Furthermore, we did not excluded companies bidding on only small markets (see 4.1.), as the focus here is on company behaviour.

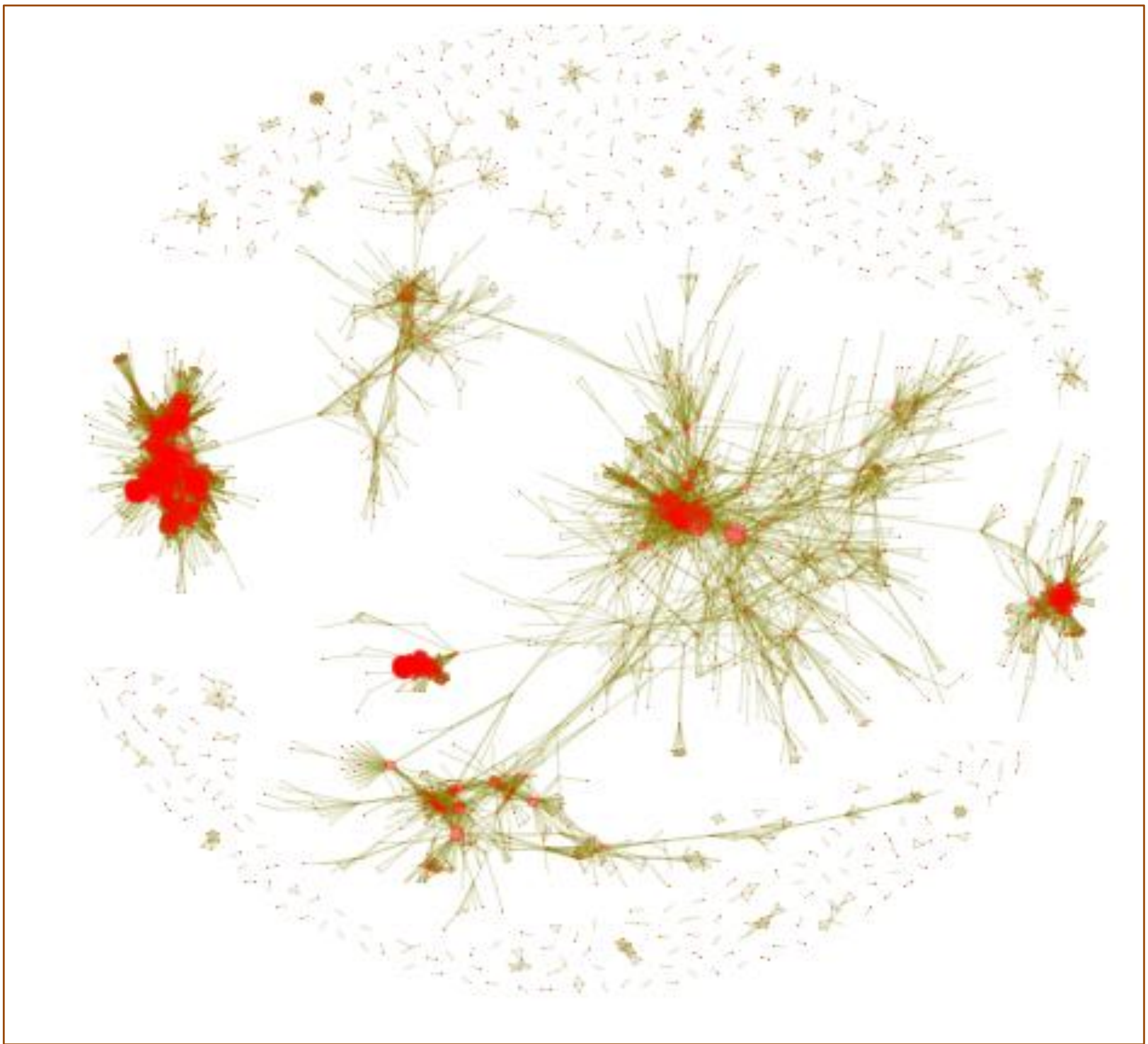
each tie represents a tender where two companies co-bid, this type of collusion would result in a so-called cut-point formation (Figure 10, right-hand side). In network terms, cut-points are vertices whose removal from the network would cut off other vertices; in other words, eliminating the cut-point would make the whole network falling into two sub-graphs (Wasserman, 1994). In such a formation, it is the cut-point which is expected to win always or almost always, while those companies which are linked to the rest of the network through the cut-point are expected to lose always or almost always.

Figure 10. Schematic representation of a cut-point network formation



As Figure 10 highlights, each of the companies may be present at multiple markets allowing for colluding and competitive behaviour depending on the market, hence the identification of the cut-point network formation crucially depends on the appropriate definition of the market companies collude in. In the absence of a robust understanding of the relevant market definition, cut-points can be sought by cycling through different market definitions from the entire public procurement market to very specific markets (Figure 11). By narrowing the market definition, the likelihood of cut-point formations increase as the inclusion of any sub-market where companies could bid competitively is becoming more restricted. Cross-referencing to other collusion indicators should guard against arriving at an unreasonably high number of cut-points and a corresponding too narrow market definition.

Figure 11. Co-bidding network of the entire Hungarian public procurement market in 2009, including markets with at least 20 contracts in 2005-2012



Note: the size of vertices show the number of times a company has won a contract.

The indicator of superfluous losing bids has to be assessed together with indicators related to the collusion types B, E and G (see Table 5).

4.2.10 Prevalence of faulty bids

Prevalence of faulty bids indicates the overly high ratio of submitted bids excluded on administrative grounds such as missing documents. Competition in procurement markets can be faked by colluding competitors submitting deliberately faulty bids. Such artificial non-competitive bids can contain deliberate errors in order to be excluded leaving only the pre-determined company with considerably higher prices in competition. As exclusion of bids based on administrative grounds is widespread in procurement markets, submitting faulty bids can still make the impression of competition, misleading contracting authorities.

Although, making errors in the submitted bids is natural, when this ratio is systematically high, or it is associated with higher prices, the suspected probability of bidder collusion is higher. This indicator is proposed by OECD (2014) and it is also part of the indicator of the Korean Competition Authority (FTCRK, 2010).

Following this logic, the authors propose the following elementary collusion risk indicator for tender i:[41]

$$PFB_i = \begin{cases} 1 \; if \; all \; bids \; are \; excluded \; except \; the \; winner's^{42} \\ 0 \; if \; there \; is \; at \; least \; two \; competing \; valid \; bids \end{cases} \quad \text{(xvi)}$$

, where 1 indicates high risk of collusion.[43]

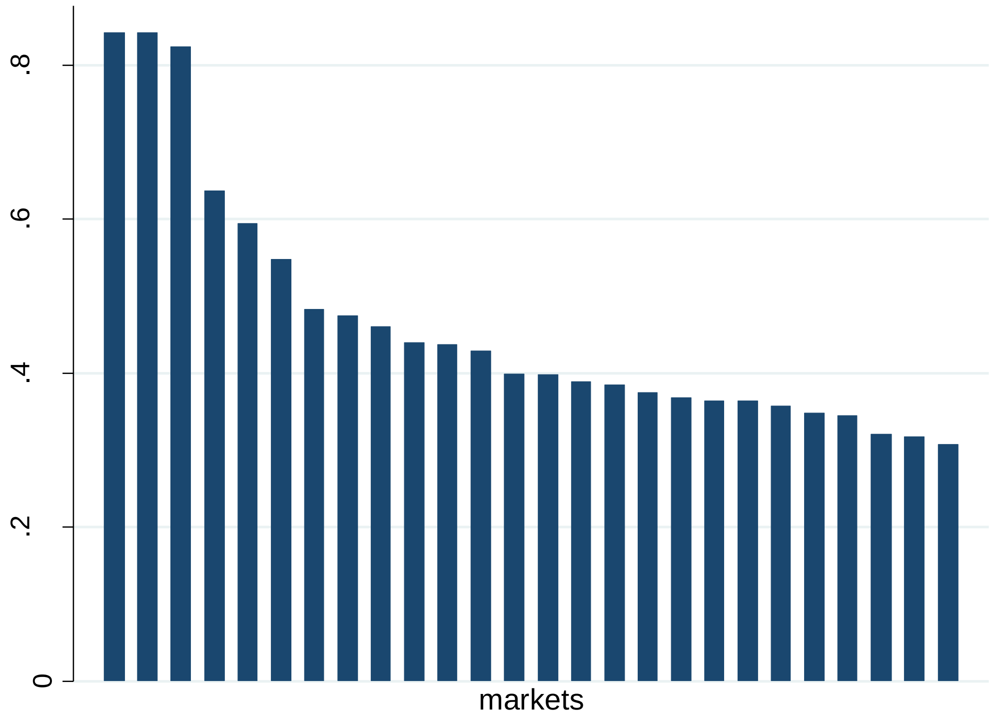
The prevalence of faulty bids cannot serve as a general indicator of collusive behaviour. It only signals collusive behaviour that uses losing bids, by using faulty offers on purpose for achieving the distorted market outcome. Therefore, co-variation between faulty bids and indicators related to collusion types B, E and G (see Table 5) have to be assessed.

An important limitation of using the high prevalence of faulty bids as a collusion indicator is that it can also signal corruption. A contracting authority can abuse the exclusion of bids based on minor formal errors in order to limit competition and support corrupt networks (Fazekas et al, 2013). The crucial difference between collusion and corruption lies in agency, who generates and classifies bids as faulty, hence excluded. Unfortunately, a single indicator cannot differentiate between actor intentions, leading to a possible upward bias when using the ratio of faulty bids as a collusion indicator. The degree of such a bias depends on the relative frequency of corrupt, but non-collusive use of disqualifying bids, which a combination alternate indices can point at.

There is significant variance among markets according to the average PFB value. Figure 12 shows that there are some markets where 30-80% of the submitted bids were excluded which is surprisingly high even for complex markets.

[41] Although all the elementary cartel indicators are defined on the level of market, the ratio of faulty bids is available on the level of tenders allowing for more fine-grained analysis.
[42] Only tenders with at least two initial bidders are considered in this case.
[43] This formula can be aggregated also yearly at market level.

Figure 12. Average ratio of faulty bids by market and year, 2005-2012 (at least 10 tenders)[44]



4.2.11 Prevalence of consortia

Prevalence of consortia indicates whether winning bids were jointly submitted by a group of companies or not. Forming a consortium undoubtedly can have efficiency gains if comparative advantages are to be exploited.[45] However, there is a less favourable motivation for consortia formation, as it can mitigate several burdens of effective collusive behaviour. First, joint bidding decreases the effective number of competing parties, which can decrease the effective competitive pressure – also in a non-collusive setup.[46] Second, joint bidding makes rent sharing significantly easier.[47] Third, bidding in a consortium also strengthens cooperation, as collusion takes place in a formal, contractual form, while in other forms of collusion, the agreement is only informal. Joint bidding is also highlighted in the OECD (2014) recommendations, as a form of rent sharing.

Besides the above theoretical foundations, competition authority decisions also highlight the possible adverse effects of joint bidding. For example, Hungarian cartel cases often included joint bidding behaviour such as “MÁV infrastructure development” and “IT systems of

[44] Only those years of a market are included, that has at least 10 tenders and the average prevalence of faulty bids is at least 20%.
[45] For example joint bidding of a foreign company with more advanced technology and a local company with the knowledge of domestic customs and institutions can have beneficial effects. For detailed discussion see Albano et al. (2009), Estache and Iimi (2008).
[46] For example, if the two lowest cost companies are colluding, then they can increase prices instantly until the third lowest cost company’s price level.
[47] Rent sharing can be made more efficient. Following Pesendorfer (2000), agreement on the completion of the different projects can be based on which company is the most efficient at the given task. Hence the obtainable rent can be increased, as implementation costs decrease.

Science Universities" (Hungarian Competition Authority Decision (HCAD) (2004) and HCAD (2007)).

Therefore, a simple indicator at a given market *m* and period *t* is the prevalence of consortia among winner bids:

$$PoC1_{mt} = Bidding\ in\ consortia_{mt} / Number\ of\ all\ tenders_{mt} \quad \text{(xvii)}$$

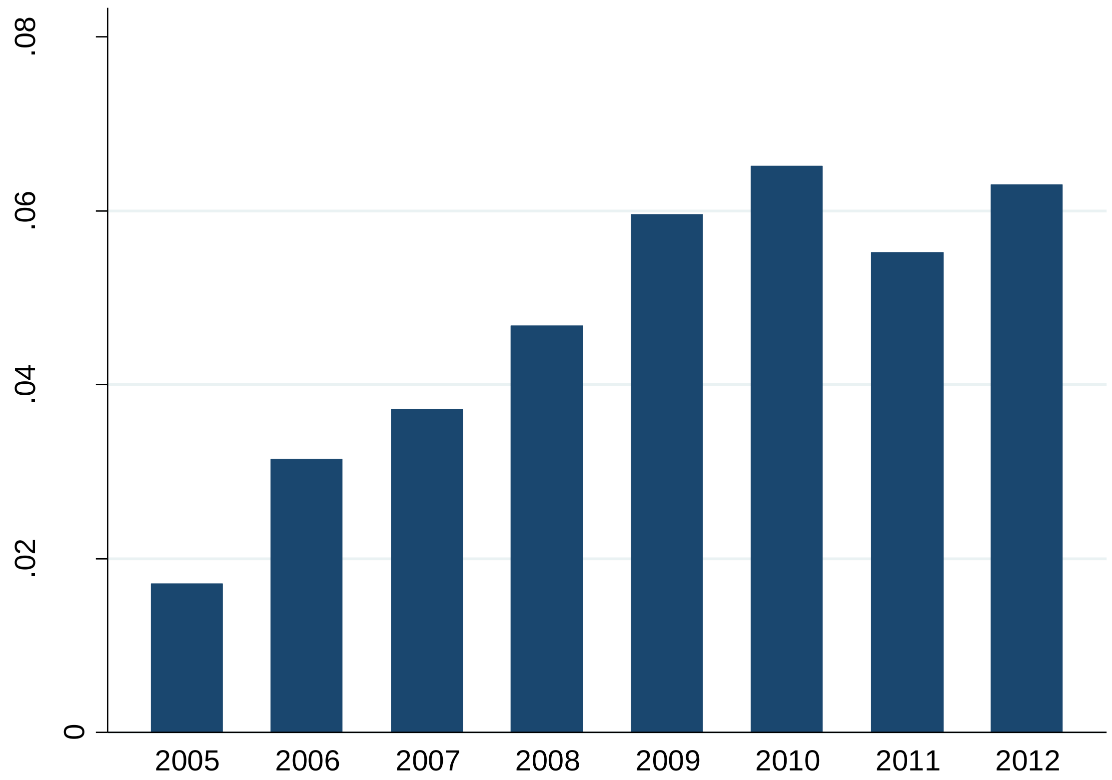
where high prevalence indicates higher probability of collusion. A more sophisticated indicator for collusion using joint bidding is when prior competing companies begin to submit bids jointly. This can be measured by the following simple indicator:

$$PoC2_{mt} = \begin{cases} 1\ if\ prior\ competing\ companies\ bid\ jointly \\ 0\ if\ competing\ companies\ do\ not\ bid\ jointly \end{cases} \quad \text{(xviii)}$$

Similarly to other indicators, prevalence of consortia cannot serve as a general indicator for collusion. Therefore, the co-variation with indicators related to cartel type C have to be analysed (see Table 5).

As Figure 13 shows, there is an increasing trend in joint bidding. However, it still affects only approximately 6% of the tenders.

Figure 13: Prevalence of consortia among winner bids by year, 2005-2012 (N=69726)



4.2.12 Prevalence of subcontracting

Prevalence of subcontracting indicates the involvement of subcontractors in contract delivery. Similarly to joint bidding, the use of subcontracts can also have an advantageous efficiency effect. However, it is also a convenient way for sharing rents among the collusive parties[48], and can also serve as a security instrument against loosing.

As already mentioned, based on Pesendorfer (2000), (possibly fake) subcontracts can also serve as a rent allocation mechanism. Furthermore, the use of subcontracts as a rent sharing tool is highlighted in OECD (2014). Regarding court judgements, many Hungarian public procurement cartels included subcontracting as a way of rent sharing (e.g. HCA (2008) "Fluor cartel", HCA (2006) "Paks Nuclear Plant – SAP, Synergon", HCA (2007) "MÁV infrastructure development").

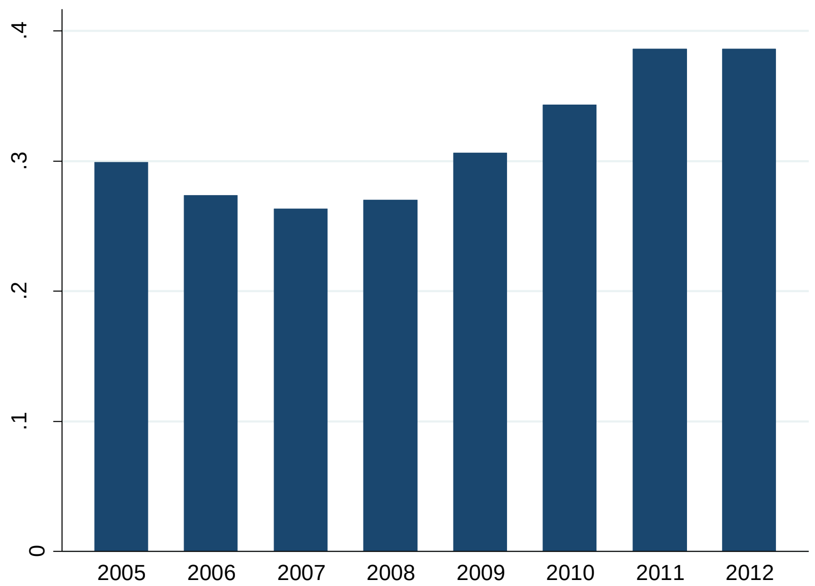
Following the discussion above, prevalence of subcontractor per market *m* and period *t* can be defined:

$$PoS_{mt} = Number\ of\ tenders\ using\ subcontractor_{mt} / Number\ of\ all\ tenders_{mt} \quad \text{(xix)}$$

The use of subcontracts have to be compared to indicators of the collusion types A, B, D and E (see Table 5).

Figure 14 shows that the prevalence of subcontracting increases over time: it is used in nearly 40% of the tenders. While it is not possible to verify the reliability of reporting subcontracting in contract award announcements, interview evidence points out that smaller subcontracts are more likely to be left unrecorded. Whereas large subcontracts, above 10% of the value of the entire contract, where the subcontractor must be named too (2011. évi CVIII. Törvény a Közbeszerzésekről), are more likely to be properly reported.

Figure 14: Prevalence of subcontracting in tender completion per year, 2005-2012[49] (N=56980)



[48] These subcontracts can be both real ones, with effective completion, but fake contracts can also serve as side-payments.

[49] Total number of cases per year: 2005: 3541; 2006: 7675; 2007: 6255; 2008: 13312; 2009: 21191; 2010: 25215; 2011: 15755; 2012: 10136.

4.2.13 Summary of elementary collusion risk indicators

Table 6 briefly summarizes the proposed collusion indicators explained in sections 4.2.1-4.2.11. The potential connections between these indicators are shown in Table 7 in Appendix A.

Table 6: Summary of collusion indicators

#	Indicator name	Short description
1	Relative contract value	The ratio of the winning bid and the prior estimated price of the tender.
2	Range of offer prices	Difference between the ratio of the winning bid and the prior estimated price and the ratio of the highest bid and the prior estimated price.
3	Difference between first and second relative offer prices	Difference between the ratio of the lowest offer price and the prior estimated price, and the second lowest price and the prior estimated price.
4	Monopolistic market structure	Indication of monopolistic market structure is the increase in one of the three following market structure indicators: (i) Market share of the largest company (ii) C4: market share of the four biggest companies (iii) HHI
5	Stable market structure	Standard deviation between time periods of three measures of market structure: (i) Market share of the largest company (ii) C4: market share of the four biggest companies (iii) HHI
6	Cyclical winning	Cyclical winning indicates whether winning bids are unrelated to prior bidding history (while controlling for other factors), hence lost tenders against certain companies in the past do not indicate present tender winning.
7	Missing bidders	Missing bidders indicates whether there is less competition because of withheld bids. We measure both market and firm level bids/tender ratios.
8	Superfluous losing bidders	Superfluous losing bidders are those bidders which only submit losing bids in the presence of one dominant company supposedly extracting rents for the whole bidding ring.
9	Prevalence of faulty bids	Prevalence of faulty bids signals tenders, where all bidding party but the winner is excluded.
10	Prevalence of consortia	Prevalence of consortia indicates whether winning bids were submitted jointly or not.
11	Prevalence of subcontracting	Prevalence of subcontracting shows whether subcontractors are involved in contract delivery.

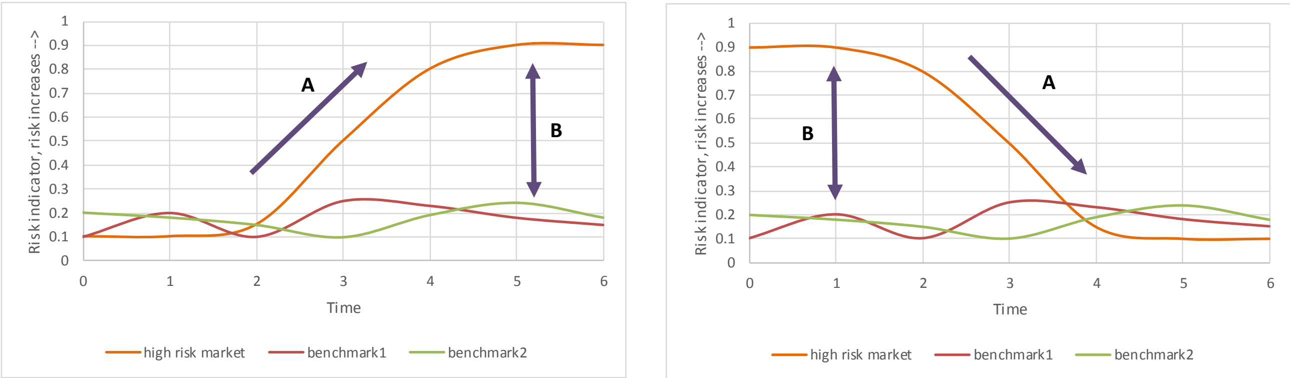
4.3 Defining benchmarks

In order to identify the values of each elementary collusion risk indicator which are more likely to indicate collusion, 'healthy' and collusive markets must be defined and compared. In the absence of 'hard evidence' such as court judgements, statistical methods can be deployed to identify deviations from 'normal' market behaviour and to define thresholds beyond which collusion risks are expected to be considerably higher. These statistical techniques exploit variation by

- time,
- geography, and
- sub-market.

For each of these three dimensions, deviations or changes can be calculated such as deviation between different geographical markets within the same product market or change over time within the same market. Then the distribution of such deviations or changes can be used either to define further continuous risk indicators or mark markets for further study. As the establishment or demise of collusive rings typically result in extremely high and/or low values of the elementary collusion risk indicators, observing the deviations across markets or changes over time of these indicators provides additional evidence for collusion. Such high risk deviations and changes are depicted in Figure 15: the left panel depicts the situation when a collusive ring is formed with the elementary collusion risk indicator starkly increasing (arrow A) which generates a distinct deviation from benchmark markets (arrow B). The right panel depicts the situation when a collusive ring breaks-up with the elementary collusion risk indicator drastically decreasing (arrow A) which does away with the formerly distinct deviation from benchmark markets. When both absolute and relative values suggest high collusion risk, the validity of measurement is strengthened.

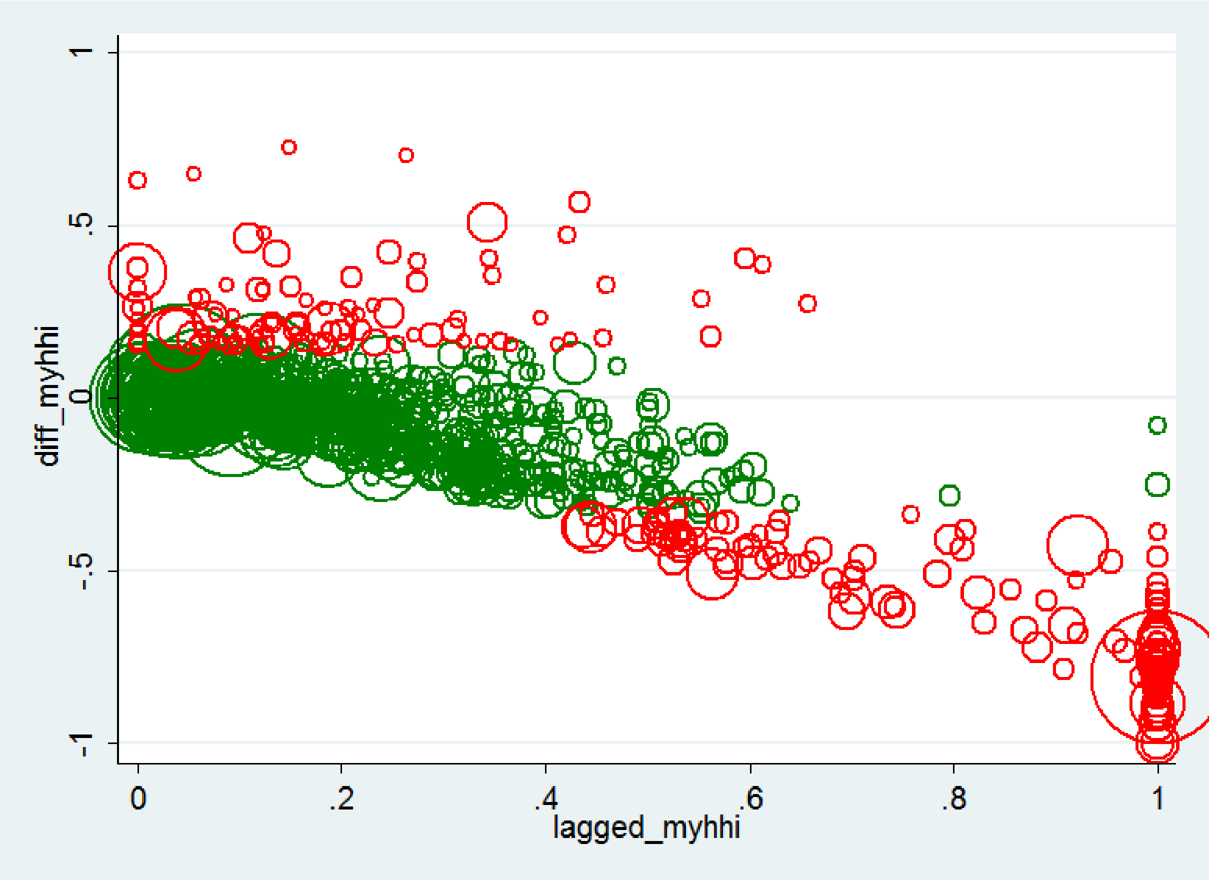
Figure 15. High collusion risk change over time (HHI): left panel suggest the creation of a collusive ring, right panel suggests the demise of collusive ring



In order to capture any distinct moves of elementary collusion risk indicators, we can simply calculate the absolute change in the score from one year to another on the level of individual markets. One such example is the absolute change in the value of HHI (Figure 16). Those markets which are highlighted in red are the ones which fit trajectory A[50] on either panel of Figure 15. It is notable that there are some quite large markets among those moving most drastically in the direction of high collusion risks (size of circles indicate the number of contracts awarded in one year).

[50] We defined extreme change in HHI within one year as a change which surpasses 0.75 standard deviation.

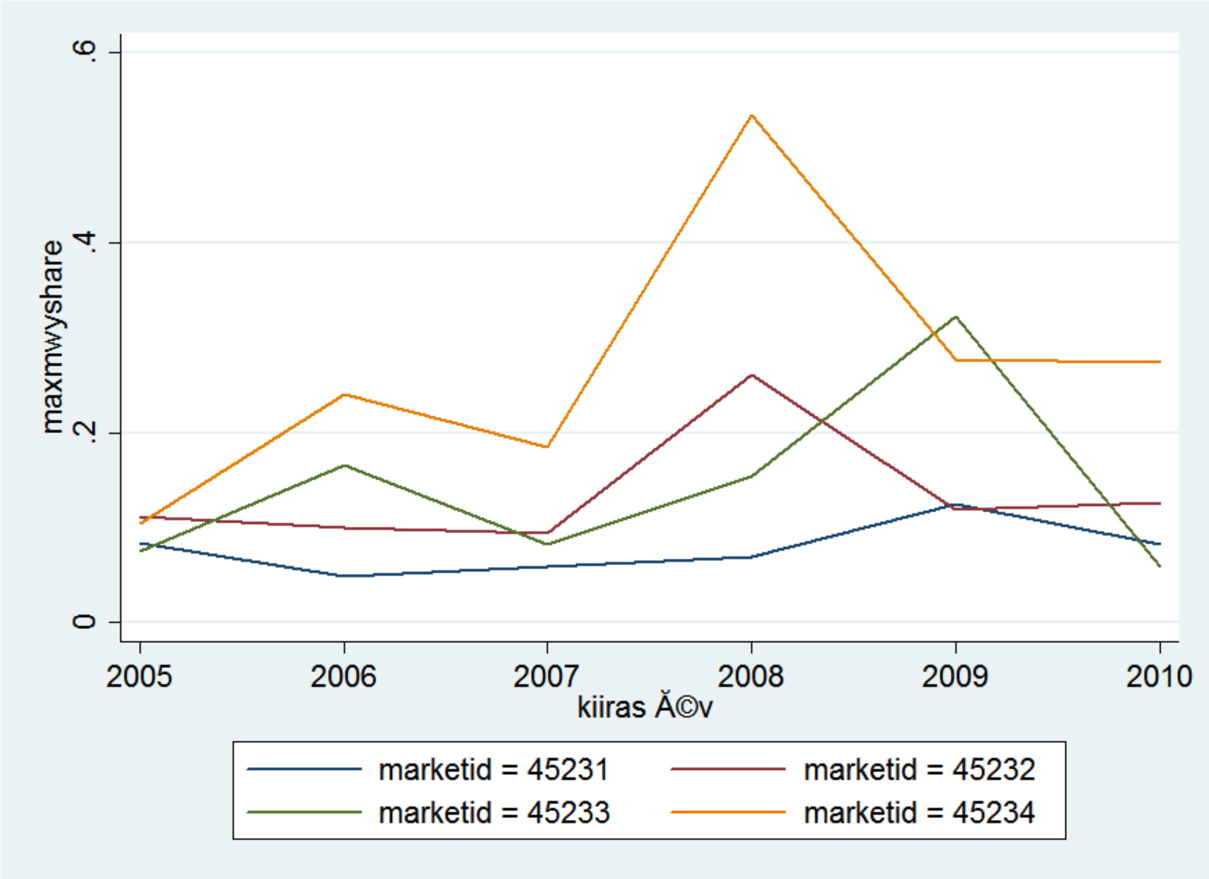
Figure 16. Markets according to their absolute change in HHI over a year and the absolute value of HHI at the start of the year, 2005-2012, Hungary (markets with more than 10 contracts in a year)



Note: size of circles indicate the number of contracts awarded in one year

To give one concrete example and demonstrate the use of benchmark markets one product market is explored with submarkets defined by major geographical regions. Due to the frequent association of roads sector with collusion, the product market "Construction work for pipelines, communication and power lines, for highways, roads, airfields and railways; flatwork" was selected. The market share of the largest company on the market ($MSoLC_{mt}$) drastically increases in two sub-markets while on marginally fluctuates in two others (Figure 17). Given that technology and spending patterns are broadly comparable on these geographical submarkets, it is possible that the changes in market structure are due to collusion. Of course a few confounding factors can also produce similar patterns, underlining the need for investigating relationships between different risk indicators and triangulating findings.

Figure 17. Market share of the largest company on the market in roads construction[51], Hungary, 2005-2010 (CPV=4523) by main region[52]



4.4 Investigating relationships among elementary collusion indicators

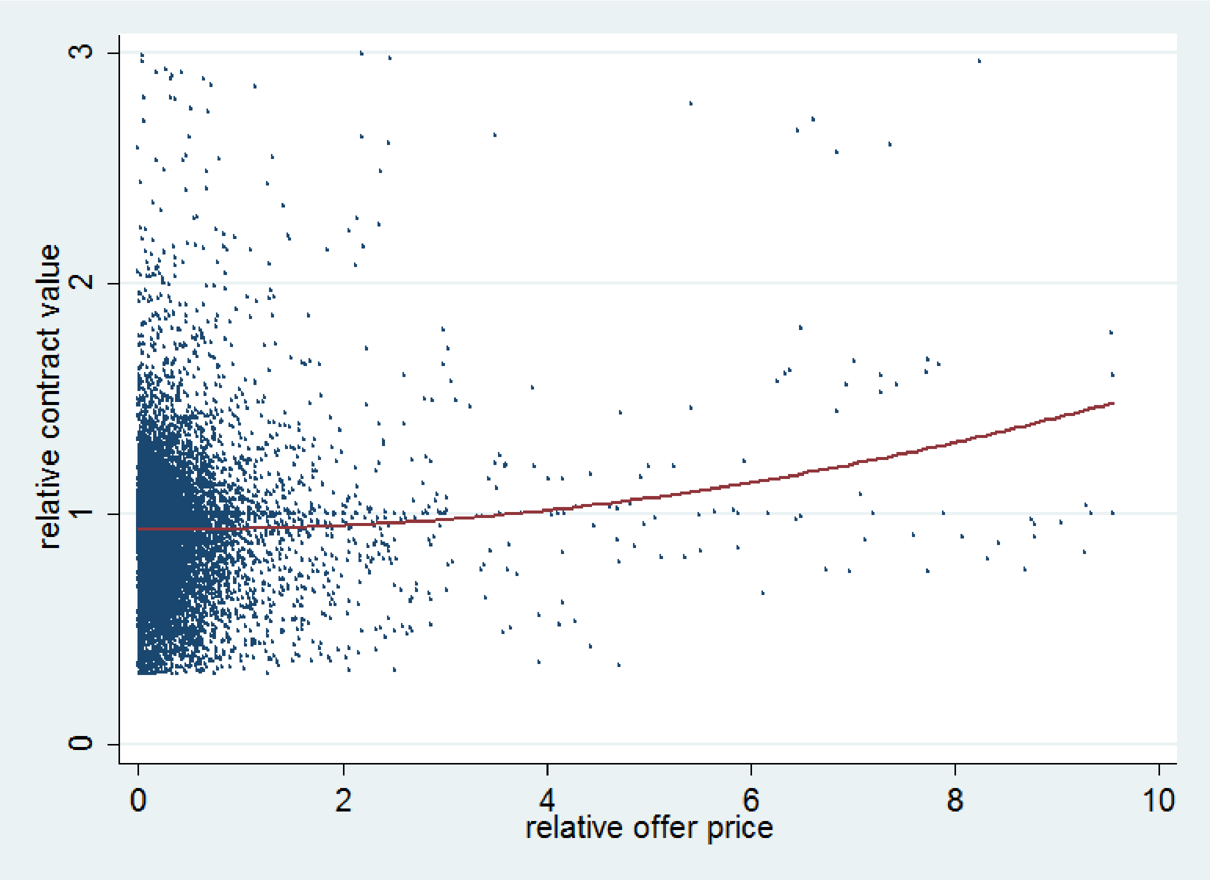
In order to identify false positives (i.e. cases where the indicators signal collusion risks while there is none) multiple elementary collusion risk indicators are combined using the expected relationships among them as defined in section 4.2.1. Recall that depending on the type of collusion, different indicators are expected to positively or negatively co-vary or be unrelated altogether.

It is possible that the elementary collusion risk indicators co-vary on the whole sample of markets and/or transactions indicating their general validity. One such straightforward relationship can be found between the range of offer prices and relative contract value with a positive correlation expected (see section 4.2.2). On the Hungarian data for 2005-2012, we find the postulated relationship on the level of tenders with particularly strong effect for the largest offer price ranges (Figure 18). These findings are also confirmed by linear regression analysis controlling for type of announcing body, year, main product market (CPV division), log real contract value (2005 constant prices).

[51] Construction work for pipelines, communication and power lines, for highways, roads, airfields and railways; flatwork

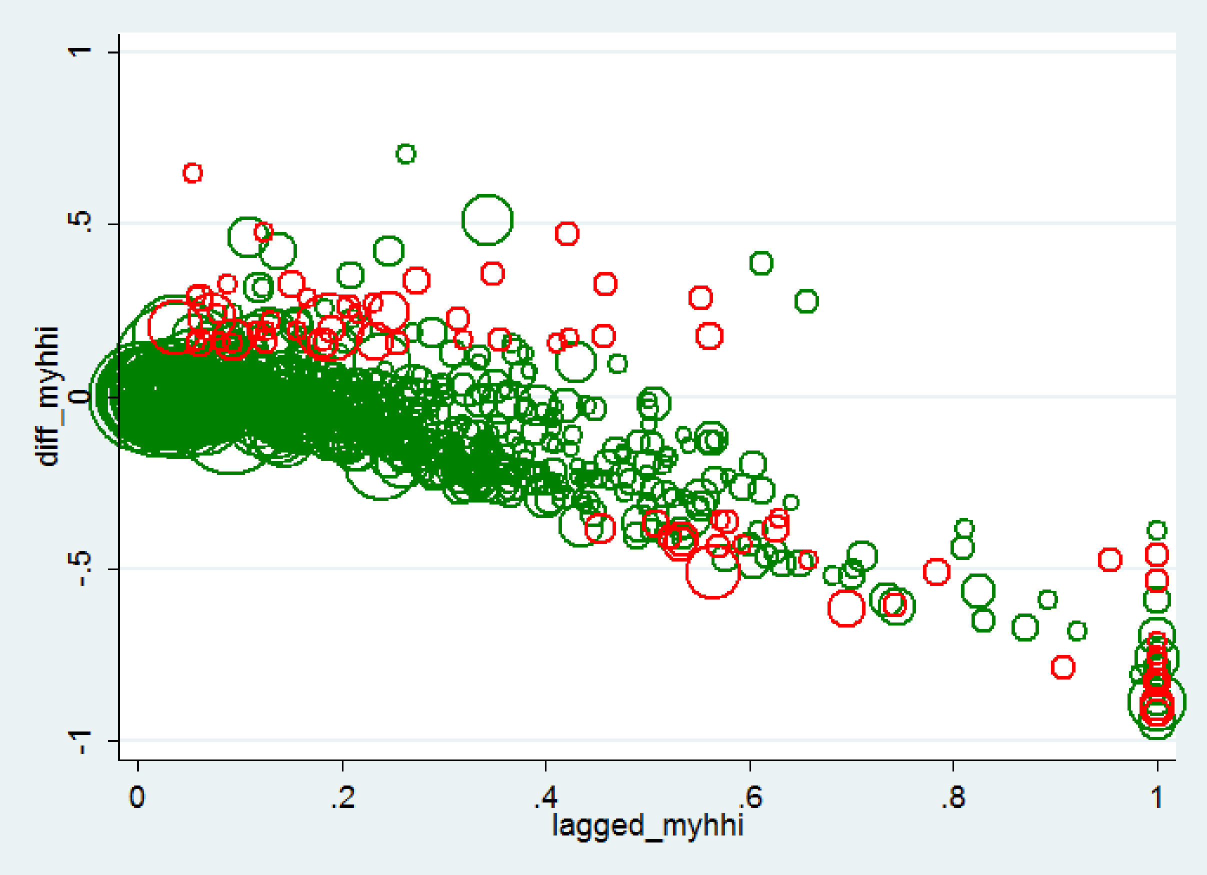
[52] West Hungary, East Hungary, Central Hungary, and contracts with national scope.

Figure 18. Bivariate relationship between range of offer prices and relative contract value, 2005-2012, Hungary, N=15,773 (0 < relative offer price < 10)



However, it is likely that some postulated relationships will not hold for the whole sample. Instead their selected values, typically outliers, in combination with other factors would still signal high collusion risk. This would indicate that they have specific rather than general validity, meaning that they can be used for measuring collusion risks, but only in specific cases and in combination with other factors. For example, HHI on the level of markets is related to relative contract value in a complex way without readily fitting into our expectations. However, for some markets the high absolute HHI, extreme change in HHI, and above average increase in relative contract value go hand in hand (Figure 19).

Figure 19. Markets according to their absolute change in HHI over a year and the absolute value of HHI at the start of the year, 2005-2012, Hungary (markets with more than 10 contracts in a year), red=high absolute HHI, extreme change in HHI, and above average increase in relative contract value



Note: size of circles indicate the number of contracts awarded in one year

Independent of general relationships between elementary collusion risk indicators, the accumulation of risk factors can signal substantially higher collusions risks, especially as evidence becomes more specific. One such example of multiple general risk factors and more specific indications of collusion risk relate to the sophisticated analysis of co-bidding patterns. On markets for road construction divided into 4 geographical sub-markets one sub-market also increased its average relative contract value between 2007 and 2009 (45233-Eastern Hungary). This market followed a distinct change in the network structure of co-bidding and the presence of cut-points (see section 4.2.7). In 2007, elementary risk indicators were fairly low: the market share of the largest company was close to the average of the other sub-markets and the relative contract value was even somewhat better than in the benchmark markets. These coincided with the almost complete lack of cut-points (Figure 20).

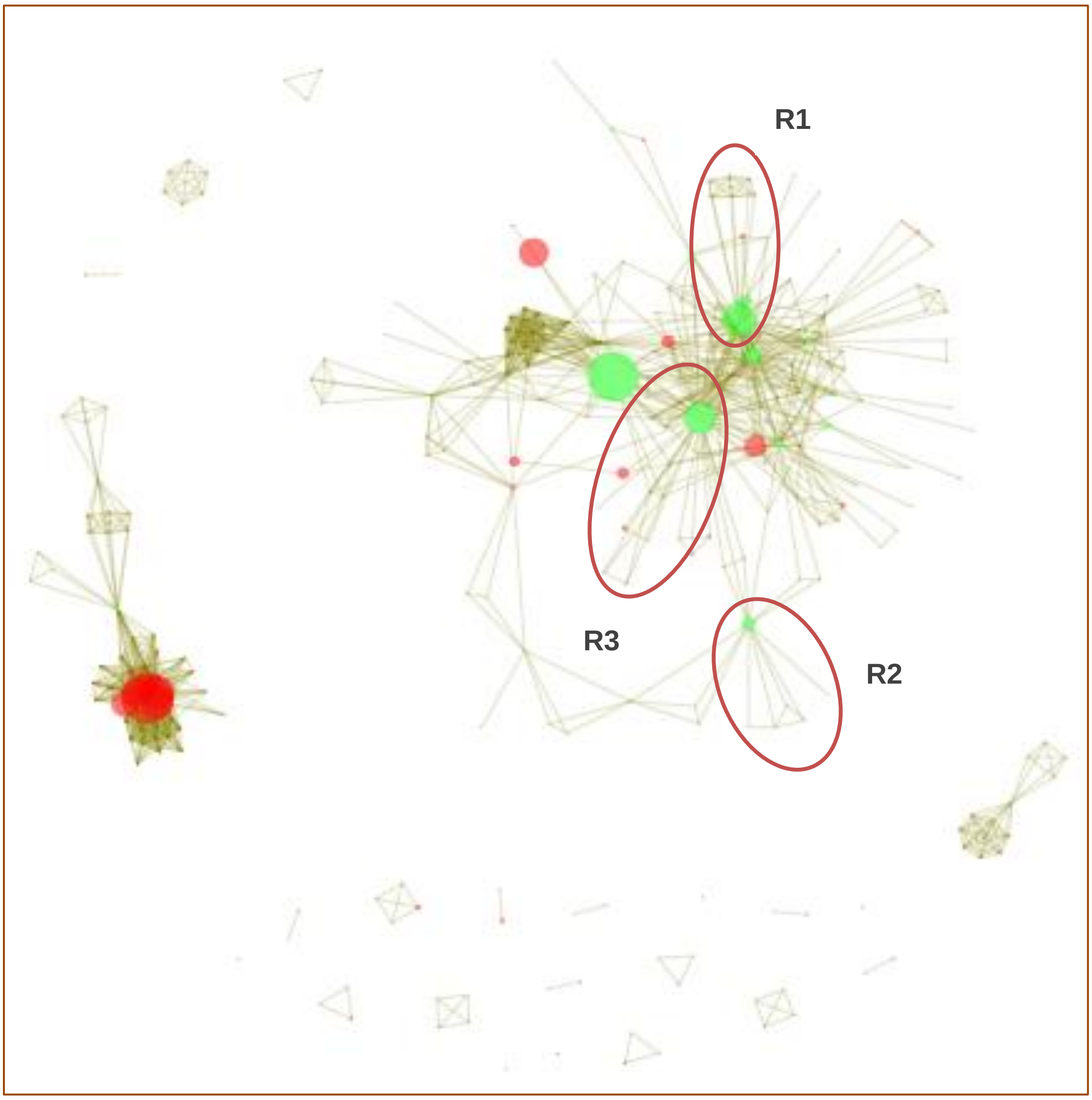
Figure 20. Co-bidding network, road construction[53], Great Plain and North Hungary, 2007

Note: node=bidding firm; node size=number of contracts won; green node=cut-point position; red node=non-cut-point position; ties=joint bidding on a tender

However, in 2009, multiple elementary collusion risk indicators suggest high risks: the market share of the largest company on the market increased drastically while the relative contract value also jumped to a much higher level. In addition, multiple cut-point formations emerged (Figure 21). In these formations (marked with R1, R2, and R3 and circled in red on the below figure), the companies positioned as a cut-points won many contracts while their smaller sub-graphs of co-bidders barely ever won. They could be considered as a bidding ring with the cut-point company collecting rents and the companies in the sub-graph submitting losing bids. Further signs of collusive bidding are higher likelihood of contract value above estimated contract value (relative contract value indicator) and more extensive use of subcontractors (prevalence of subcontracting indicator).

[53] CPV= 4523: Construction work for pipelines, communication and power lines, for highways, roads, airfields and railways; flatwork.

Figure 21. Co-bidding network, road construction[54], Great Plain and North Hungary, 2009



Note: node=bidding firm; node size=number of contracts won; green node=cut-point position; red node=non-cut-point position; ties=joint bidding on a tender

4.5 Assigning collusion risk scores

The above has pointed out how elementary collusions risk indicators can be used in isolation as well as in combination to gauge the risk of collusion by collusion type. While there is great advantage in keeping elementary indicators distinct for screening and other purposes, in some cases a simple composite score may be needed. Such case could be when scarce investigative resources have to be allocated to different cases requiring an informed assessment of the overall likelihood of establishing collusion in different markets.

In general, there are two distinct options for assigning collusion scores:

- Categorical collusion score, and

[54] CPV= 4523: Construction work for pipelines, communication and power lines, for highways, roads, airfields and railways; flatwork.

- Continuous collusion score.

In its simplest form, the categorical collusion score can take the value of 0 or 1 with

$$CRS_i = \begin{cases} 1\ if\ at\ least\ two\ elementary\ risk\ indicator\ signal\ similar\ collusion\ behavior \\ 0\ if\ there\ are\ no\ two\ elementary\ risk\ indicators\ signal\ similar\ collusion\ behavior \end{cases} \quad \text{(viii)}$$

Where *i* can denote tenders, company-period observations or market-period observations depending on analytical needs. The categorical indicator can be further refined into a 'traffic light' system where the accumulation of multiple elementary collusion risk indicators are captured by higher order risk categories.

The continuous collusion risk score is best calculated as the weighted average of all the relevant elementary risk indicators to the collusion type in question. Recall, different types of collusion can be tracked with a different set of indicators making the construction of a single score a delicate exercise (Table 1). Nevertheless, it is possible to derive a continuous collusion risk score:

$$0 \le CRS_i \le 1 \quad (ix)$$

where 0=minimal collusion risk and 1=maximal observed collusion risk. It is defined by the following formula:

$$CRS_i = \Sigma_j\, w_{jt} * CI_j / N^{CI}_t \quad (x)$$

Where *i* can denote tenders, company-period observations or market-period observations depending on analytical needs; w_{jt} is the weight of the *j*th elementary collusion risk indicator for collusion type *t*, CI_{jt} denotes the value of the *j*th elementary collusion risk indicator; and N^{CI}_t is the number of elementary collusion risk indicators relevant for collusion type *t*.

As further work is needed to fully grasp the relationships between elementary collusion risk scores and hence to define the exact formula for CRS, no empirical example is provided in this working paper.

5 Instead of conclusions: the way forward

This paper has travelled a long way to collect, evaluate, and synthesize over two decades of work on public procurement collusion. While this is still work in progress, a few milestones have been achieved:

- A broad list of individual or elementary collusion risk indicators could be precisely defined and implemented in the Hungarian public procurement database. This amply points out how the advance of public procurement data collection techniques and diverse analytical tools have led to a fundamental change in the measurement of collusion risks across the globe following a unified template.
- The relationships between elementary collusion risk indicators could be defined and explored. With the help of two concepts: general and specific validity insights have

been gained on the scope of applicability and the most efficient use of individual indicators. Some appear to be of a more general character while others are only reliable in the presence of other risk factors.

- An attempt at constructing summary scores have been made, though much more work is required. The construction logic is set out precisely, while it remains to empirically evaluate alternative approaches.

While much has been achieved there is much left to do. First of all, different composite scores shall be calculated and their relative performance compared, for example by invoking proven cases of collusion. Second, there are a few additional promising indicators which can calculated on globally available public procurement databases; hence could potentially be included in this discussion. These additions to the list of elementary collusion risk indicators will be carefully evaluated. Thurd, while the primary aim of this paper was to elaborate a pilot study using one country's public procurement data, the ultimate goal is to implement these and similar indicators in every developed economy, with particular focus on the EU, South Korea, and the US which have high quality and accessible public procurement data.

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Appendix A

Table 7: Connection between elementary collusion indicators

	Relative contract value	Range of offer prices	Difference between first and second relative offer prices	Monopolistic market structure	Stable market structure	Cyclical winning	Superfluous loosing bidders	Prevalence of faulty bids	Prevalence of consortia	Prevalence of sub-contracting
Relative contract value		X	X	X	X	X	X	X	X	X
Range of offer prices	X		X	X	X	X	X			X
Difference between first and second relative offer prices	X	X		X	X	X	X			X
Monopolistic market structure	X	X	X				X	X	X	X
Stable market structure	X		X			X		X		
Cyclical winning	X		X		X					
Superfluous loosing bidders	X	X	X	X	X					X
Prevalence of faulty bids	X			X	X	X				X
Prevalence of consortia	X			X						
Prevalence of subcontracting	X	X	X	X			X	X		