The changing face of anti-trust in the world of Big Tech: Collusion versus Monopolisation*

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Abstract

This paper presents new evidence on two key developments in worldwide anti-trust in the last decade: (i) a downturn in the number of cartels detected by competition authorities, alongside (ii) exponential growth in cases of monopolisation/abuse of dominance. Big Tech firms have been, undoubtedly, the main focus of the latter but almost totally absent in the former. These two developments offer perspectives on the description of *Monopoly Capitalism* as set out by Keith Cowling forty years ago. Superficially at least, this seems to deny the prediction of ever-widening collusion, but, on the other hand, it resonates with the prediction of increasingly unassailable dominant firms. We suggest that the two trends can best be understood by the emergence of the Big Tech giants who have established dominance by exceeding tipping points in many markets. In turn, this leads to an alternative form of collusion —"mutual forbearance" in which firms back away from aggressive competition in the other giants' areas of strength. Given this dominance, they do not need collusion —put simply, no sizeable rivals are remaining with whom they need to collude.

Keywords: algorithms, cartels, deterrence, enforcement, monopolisation
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‡Co-author Professor Stephen (Steve) Davies was keen to contribute to this volume as he was a student at Warwick in the late 1960s when Keith Cowling was first building a research group in industrial economics. Steve made work on this paper fun, but sadly he passed away just hours after we received feedback for the final revision of this paper. He had been looking forward to taking up a Leverhulme Fellowship in the autumn and even in hospital, on his last day of life, he was talking about competition economics. We, and the community of industrial economists, will deeply miss him. We like to think that Steve has now joined Keith for high-intellectual debates on the functioning of markets (of course, as well as Arsenal and Coventry City). Steve, great colleague and dear friend, rest in peace.

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1 Introduction

This paper is motivated by the opening page of *Monopoly Capitalism*[19] which proposes that "Major corporations are now organised in, often interlinked, oligopoly groups ... and have captured dominant positions which are relatively unassailable. The norm in such an oligopolistic world will be collusion".

We return to this vision with the benefit of four decades of hindsight and drawing upon four contemporary bodies of literature. The first is from the relatively narrow field of Industrial Organisation (IO) and Competition Policy, building on the empirical observation of a decline in recent years in the USA in the number of cartels detected and prosecuted by the competition authority (CA). The evidence is piecemeal and so the reasons why are still open. Moreover, it has yet to be established whether the USA is singular, or representative of a more worldwide phenomenon. The second is more wide-ranging with some of the most important contributions coming from outside IO by macro, labour, and development economists. This is the claim that concentration and mark-ups have both been increasing rapidly in recent years in the USA and (less certainly) in the rest of the world. This, it is argued, signals the demise of competition, with ever more dominant oligopolists increasing their market power in many markets. The third derives from the major technological innovation of our age, artificial intelligence (AI), and machine learning, and its implications for the nature of competition between firms —for example, how the tools of AI can be used for personalised pricing and sophisticated algorithmic pricing capable of sustaining price-fixing without the need for formal, and illegal, cartels. Relatedly, the fourth literature concerns whether the emergence of the giants of Big Tech, based partly on the new business model of digital platforms, has contributed to the process of monopolisation, as these have high fixed setup costs and very low, if not zero, marginal costs, leading to high economies of scale and scope. This process of monopolisation is enhanced by the value of data. The Big Tech companies operate as digital platforms, and can exploit a large base of users by collecting data that they can use to improve their service and, in this way, expand the user base. They can also sell data to advertisers or other companies and generate revenues to be spent on service quality improvement. This feedback loop acts as a barrier to entry to possible competitors protecting the monopoly power in the market. This cost structure together with direct and indirect network effects and the value of data result in concentrated markets in the hands of one or very few companies, up to the point that there is a growing consensus that digital platforms are the new form of monopolies.

Our empirical work contributes mainly to the first body of literature, and reflects on Cowling's assessments and predictions by assembling two new pieces of evidence. These are both based on statistics concerning the interventions of CAs from around the world. The first is international panel data to test, with no claim of causation, whether there has been an inverse-U profile of the number of cartel detections in recent years. It confirms that this is the case for both the USA and more generally worldwide. It then contemplates alternative explanations. One possibility is that the antitrust policy is working and falling detection rates reflect increasingly strong deterrent effects. But other, far less favourable explanations are also possible. Perhaps cartelists are becoming more adept at concealing their conspiracies and the declining number of detections reflects increasingly ineffective competition authorities. This would provide further evidence for the "demise of worldwide competition"; indeed, it would widen the evidence beyond just merger control to also include cartel enforcement. Alternatively, it may be that the number of cartels (whether detected or undetected) is declining, not because anti-competitive behaviour has been eradicated but more because it now takes other forms. This might reflect an increasing switch to tacit collusion facilitated by algorithmic pricing —not illegal but no less harmful to consumers. Or it might be because leading firms now no longer need to rely on collusion to exploit their market power. After all, they have become increasingly (and singly) dominant in their own right. In the parlance of Competition Law, there is an increasing switch from anti-competitive agreements (collusion) to single-firm monopolisation (or abuse of dominance). There is then the aspect that an increased number of single-firm monopolisation cases puts a burden on CAs' cartel decisions, as they have limited resources after they deal with the merger notifications. Therefore, they need to set priorities. At one time, these may be focused on cartels, at another on monopolistic abuse. It is likely that if one increases, the other will decrease.

This second piece of evidence pursues the fourth of these alternative explanations for apparently declining cartel activity, by assembling evidence of an ever-increasing number of enforcement cases for abuse of dominant positions or single-firm conduct against the GAFAM firms (Google, Apple, Facebook, Amazon, and Microsoft), which personify "Big Tech". Here the evidence is striking: in direct contrast to declining numbers of detected cartels, the number of monopoly abuse investigations has exploded exponentially in recent years (see also [43]).

Following the Literature Review section, the rest of the paper proceeds as follows. Section 3 addresses the primary descriptive objective. For a sample of 32 competition authorities throughout the world, we construct a consistent panel database for 2006-2018. This confirms that in both the USA and the world as a whole, there was an increasing number of cartels detected for the first half of the period but then a decline in the second half—we refer to this hereafter as the "inverse-U" shape. The rest of the paper assesses potential alternative explanations. The simplest is that we are observing a secular trend throughout an integrated world economy, perhaps reflecting macro forces not necessarily related to anti-trust problems and policies (e.g. the financial crisis or, more generally, the world business cycle.) Alternatively, the inverse-U may reflect shifts in the US policy regime which have had immediate spillovers to other countries, leading to very similar time profiles of cartel enforcement to those seen in the USA. This might reflect the leading role played by the Department of Justice (DoJ) in detecting and prosecuting cross-jurisdictional multinational cartels, facilitating prosecution in other national CAs. To the extent that this was true, to explain systematic worldwide trends, we might need to look little further than institutional/political policy changes over these years within the USA. The section also describes the collection of data on enforcement decisions around the world, limited to single-firm conduct (abuse of dominant position in Europe) by the top digital platforms. The coverage is the period 2000-2020.

Section 4 explores the evidence in more detail, focusing first on cartel behaviour and then on enforcement of single-firm conduct due to the rising market concentration, largely caused by the digitalisation of the economy. It gives intuition of how policy experience might impact cartel enforcement, formation, and deterrence over the lifetime of a CA. It shows how an inverse-U in the number of enforcement cases could be consistent with a strong deterrent effect: if the probability of detection increases as the CA becomes more experienced over time, and if its successes in enforcement feedback into increased deterrence. An empirical implication of this model is that the number of detected cases should be plotted not against calendar time per se, but rather against the age of the CA.[1] This distinction becomes important in an international panel database such as this, in which national CAs differ in their maturity, and therefore lie at different points in their life cycles. This suggests a simple test for the model: against a 'one-curve-fits-all' default, there should be a superior empirical fit if we allow for heterogeneity in the maturity of CAs over time. The intuitive model is specified and tested empirically using the international panel data. This confirms that the number of cartels detected does indeed follow an inverse-U profile and that the best fit is achieved when plotted against the ages of the individual CAs. This result remains robust to the inclusion of other explanatory variables. However, as mentioned earlier, this result does not claim causality but only association because there are many underlying reasons behind this inverse-U shape, which we refer to later. The section then turns the attention to the issue of rising concentration in markets and provides a discussion of the evidence of enforcement of single-firm conduct. The nonlinear trend of enforcement cases is striking.

Section 5 discusses the implications. What seems indisputable is that there has been a shift in the mix of anti-trust interventions by CAs throughout the world: cases of abuse

[1]Strictly speaking, we measure the age of the country's cartel law, rather than the CA itself, since we are interested specifically in the development of cartel policy rather than competition policy in general. In most countries, the cartel law was introduced simultaneously with the creation of the CA; but where not, we record the age of the cartel law, although hereafter in the text we refer to CA age or cartel age.

of single dominance, especially by the GAFAM big tech firms, are expanding exponentially, whilst cartel interventions are on the wane. We consider alternative potential explanations. We close the paper by returning to Cowling —how might he have explained the facts we and others have uncovered?

2 Literature review

As a preliminary to reviewing the recent literature, we begin with a concise résumé of Cowling's main arguments/predictions. Perhaps best known is his quotation at the start of our paper: "the largest firms increasingly capture dominant positions which makes them unassailable in their spheres of control and discourages rivals from engaging in aggressive moves against them." The key here is the fear of "tit-for-tat" retaliation —collusion emerges precisely to avoid the self-destructive rivalry amongst the largest firms. In hindsight, his intuition anticipated game-theoretic explanations of tacit collusion as the equilibrium outcome of potentially fierce repeated games. An extreme form of this outcome occurs when there is mutual forbearance —firms do not even enter each others' markets (or only in a tentative way) thereby each ceding to each other market power in its backyard. For Cowling, an important explanation for how this dominance emerges is a strategic investment (typically by advertising and more broadly marketing) designed to differentiate the firm's products from its potential rivals and thereby reduce its price elasticity ([17]). Two key empirical predictions of Cowling (and others at that time) were that concentration levels and price-cost margins would both inexorably increase over time ([16], [18]).

Against this backcloth, Cowling's predictions and insights remain as relevant today as they were forty years ago.

A more recent and broader context for the current paper derives from the growing and controversial works of literature on falling levels of competition within US markets and in other countries. Empirically, this has invoked evidence of medium to long-term trends in the macro shares of corporate profits and labour; surrogates for price-cost margins; and structural measures—predominantly concentration. The recent literature on the growth of concentration is voluminous, (see [21] and [46] for summaries). In the UK for example, using an HHI measure of concentration at four-digit Standard Industry Classification (SIC), [21] estimates (his Fact 1) that typical industry concentration increased rapidly by about 30%, between 1998 and 2011 before levelling off at its new higher level, 2011-2018. For the US economy, using a similar measure of concentration but restricted to the US publicly traded firms available from Compustat and with an analysis conducted at the three-digit North American Industry Classification System (NAICS), [34] show around 70 per cent increase between 1997 and 2014 (see their Figure 1A). Likewise, [35], using the same data and level of aggregation, found that the mean HHI increased from 0.12 to 0.18 between 1995 and 2012 (about 50% growth between the two periods, as documented in their Figure 1B). Though there is agreement on the increase of concentration in the US, studies relying on the more comprehensive US economic census dataset at SIC-4 of NAICS-6 and using metrics of top firms document a smaller magnitude of the rise. [36] confirm a 4 to 6 per cent increase in CR8 between 1998 and 2012 (their Figure 26). [54] with their matching of data over time quantifies an average 21% increase in CR4 (18% in CR8) between 1997 and 2012 (their Table 3). [24] document a growth rate of about 8% and 10% in CR4 and CR20 between 1998 and 2012 (their Figure 1A). A summary of the percentage point change in market concentration by sector for CR50 between 1997 and 2012 is available in Table 1 of [57].

Various commentators, including notably [48] have interpreted this as evidence that markets and competition authorities are not functioning well, especially with respect to lax merger control. Others ([6]) argue, on the contrary, that evidence points to the emergence of a new breed of firm —revolutionising markets and competition —the superstar firm. Competition Authorities around the world have also taken an increasing interest. In the UK for example, the report by [12] estimated similar increases in concentration to those reported by [21].

Digital platforms operated by Tech Firms have contributed to this process [53]. Explanations of these trends are various and by no means all agree that competition is falling (see, for example, [24].) However, one important theme in this literature is that competition policy has become increasingly ineffective in protecting competition. Two influential, and particularly critical voices from Shapiro are [p.91][48], who suggests that "what is undeniable, however, is that mergers have been allowed to proceed at an unprecedented pace, which has significantly contributed to a rise in concentration in the US", and [Preface][41], who bemoans the adverse effects of an "increased permissiveness of antitrust policy (in merger control) over the past twenty-five years". [p.73][52] in a recent symposium also points the finger at a "gradual weakening of merger control" and identifies "a need for stronger merger enforcement ... with Superstar Firms" [p.75]. In his case, the analysis is not confined to just merger control but also extends to anti-competitive behaviour by dominant firms ("monopoly abuse".) However, even from Shapiro's wider perspective, as he admits, he "does not address one core aspect of antitrust enforcement: the prohibition on cartels and price-fixing" [p.72]. While he observes that "Improved detection of active cartels would do much to promote competition", he does not explore the evidence of changing levels of cartel enforcement. Thus, one objective of the current paper is to complement the extensive empirical literature on merger enforcement with comparable evidence of activity in another of the key areas of competition policy, cartel enforcement.

The specialist Industrial Organisation (IO) and Competition Policy pieces of literature include few empirical longitudinal studies of cartel enforcement, and a shortage of genuinely comparable intertemporal and/or international data appears to be the major reason. [13] draws on various pieces of descriptive evidence, from global law firms, the US Department of Justice (DoJ), and his own "Private International Cartels dataset" to support his claim of a downturn in recent years in the number of cartel enforcement cases, but the time series are typically very short.

Beyond this, there is very little in the regular IO field journals, and only two studies stand out as directly relevant for present purposes. First, [32] conducted a time series analysis of various indicators of historical DoJ enforcement activity (1969-2012) in the USA. On a descriptive level, they highlighted three sub-periods: pre-1980, there were only a relatively small number of cases detected, but 1980-95 then saw a dramatic rise, before numbers fell back 1995-2012. Their econometric analysis is confined to a first-order auto-regressive equation, including dummy variables for sub-periods of different severity in punishment and leniency. The latter variables were not statistically significant, and their results were dominated by a strongly significant one-year lagged dependent variable, with an estimated coefficient in the region of 0.8. These results do not establish an inverse-U but only a concave monotonic declining function against time. More recently, the authors have returned to the subject, [33], with a more complete econometric model and data extended to 2016. Again, their interpretation of the descriptive data is that "DoJ Antitrust is prosecuting fewer cartels. This has been the case for several years, aside from the increase under the Obama administration" [p.495]. Their econometric model is again dominated by a lagged dependent variable. This now attracts a reduced coefficient of less than 0.5, which is consistent with a more pronounced slowdown over time, but not any turning point. However, they also include 'policy' dummy variables which segment the period into four sub-periods, which reveal increased numbers in the early years but declining in later years. The time-series implications of this estimated model are a little ambiguous, in that a step function is superimposed on an underlying concave monotonic time function, and graphically this gives rise to a rough inverse-U time path. The authors' explanations reflect this, with a mix of hypotheses, some of which are institutional and US-specific, such as president-identity and judgements about tightening/loosening of the US competition regime. Others are more general and less US context-specific, positing underlying tendencies such as increasingly effective deterrent effects or increasingly sophisticated cartelists in concealing their conspiracies. Their study focuses mainly on US experience, but they do report one other finding, [33] [p.507] relevant for our international study: "we do not find any obvious interrelationships between US and

EC cartel prosecutions, based on aggregate enforcement data".

Turning to Big Tech, and particularly digital platforms, inevitably in their day-to-day business of collecting and storing data to improve their service or for sale, they have developed sophisticated algorithms which potentially support stable tacit collusion and effectively weaken competitive pressures without the need to resort to the formal illegal cartel behaviour. As pointed out by [10] in their critical review of the law, economics, and computer sciences literature, there is growing concern among scholars (e.g., [11]) and competition authorities on the ability of pricing algorithms to sustain collusion. The evidence of the effectiveness of algorithms in providing stable collusion is studied experimentally by [9], where they find that algorithms sparked by artificial intelligence can maintain prices above the competitive level without the need for communication, as long as firms can observe each other's prices. [37] extends their experiment by removing the need of observing competitors' prices, and finds that in this case too, collusion is possible. A less alarming view of the competition is presented by [45]. They suggest that algorithms lead to superior demand forecast, and this feedbacks in pricing performance, which can lead to lower prices and gain in consumer welfare. A contrasting view is portrayed by [40], where they argue that as classic collusion was unstable, algorithmic collusion will be too as it does require coordination in the exchange of information between algorithm designers.

[38] describes conditions when algorithmic collusion can be treated as unlawful and makes the point that in the US, the law focuses on the existence of 'agreeing or conspiring'. In most jurisdictions around the world, any kind of coordination or exchange of information relating to pricing intention, customer allocation or anything else that reduces the risks of competition, is unlawful. These prohibitions are not generally concerned with the effect of the collusion or whether it was implemented, and to escape liability the parties must generally demonstrate an efficiency-based defence or that the arrangement comes under a specific exemption, such as those relating to research and development joint ventures or, more recently, environmental motives.

3 Data and descriptive facts

Our first objective is to review the descriptive evidence on cartel enforcement, measured by the number of cartels prohibited in recent years. Is there indeed an inverse-U time profile in the US data, and, if so, is there a similar pattern for the rest of the world? For this purpose, to our knowledge, the most broadly consistent data source available, that annually provides data for a large number of countries is the Global Competition Review (GCR). We complement this proprietary data source with additional information obtained from World Bank Indicator Catalogue, American Bar Association Book on Competition Law and Policy, and Common Law Jurisdictions by [55], The Design of Competition Law Institutions by [28], and then competition authorities' websites to fill the gaps.[2] These combined datasets allow us to construct a panel on an annual basis for 13 years (2006-18) for a cross-section of 32 competition authorities (CAs).[3] Although the time series is relatively short,[4] cross-sectional variation in the ages of the CAs is considerable (the cross-section standard deviation is 25.98), and this provides the equivalent to a longer-term dimension to the data (see Table 1). Figure 1 shows the aggregate counts for the USA and the 31 other countries (using a three-year moving average).

As can be seen, in both the Rest of the World and the USA, there were two distinct sub-periods: initially, steady year on year increases up to 2011/2012, but thereafter year on year decreases. The two time series run broadly parallel.

We interpret this as preliminary descriptive evidence of an inverse-U time profile, and one which is not just US-specific,[5] but shared across the world. The fact that this is indeed

[2] A small amount of interpolation has been made for missing years.

[3] Data availability determines the period and number of countries. These are all countries for which comparable time series are available in the GCR enforcement reports: Australia, Austria, Belgium, Brazil, Canada, Chile, Czech Republic, Denmark, EU, Finland, France, Germany, Greece, Hungary, Ireland, Israel, Italy, Japan, Lithuania, Mexico, Netherlands, New Zealand, Norway, Pakistan, Poland, Portugal, South Africa, Spain, Sweden, Switzerland, UK, USA.

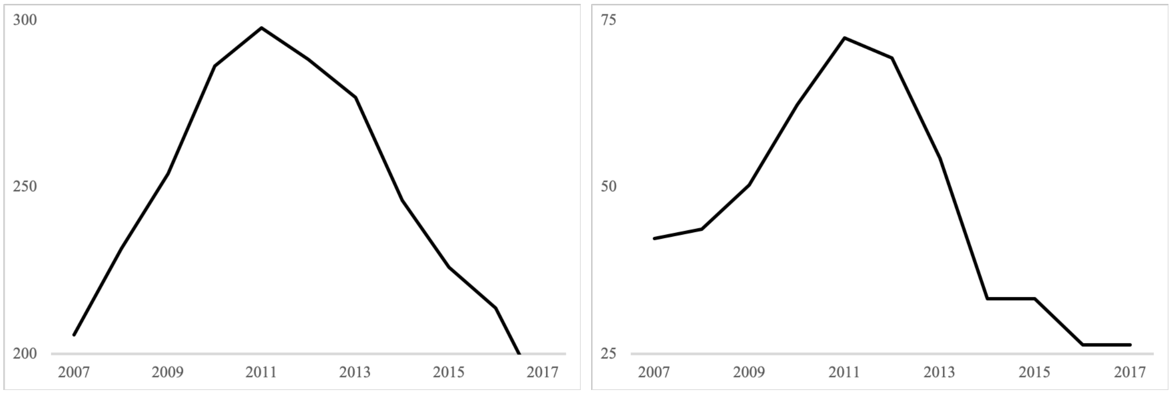
[4] [46] has also recently started to publish international data, but as yet these only cover four years, 2015-18, which is insufficient for our purposes.

[5] For the US, the peak in counts is 2011. The decline is sharper vis-à-vis the rest of the world. A lot is going on at this time. The obvious event is the collapse of US banking, deep equity market declines, the housing collapse, Freddy and Fannie's nationalisation and subsequent unprecedented macro quantitative

Table 1: Variable definitions, data sources and descriptive statistics

variable	definition & source	mean	sd
	continuous variables (country i and time t)		
cartels+	Number of cartels prohibited‡	10.74	15.74
age++	Number of years of cartel law†	42.2	25.6
lngnipi	GNI per capita (euros, natural log)‡	35157	20574
lnmerger	Number of mergers notified to competition authority (natural log)‡	255.3	375.7
lnprison	Maximum years of imprisonment (natural log)‡	3.40	3.94
	binary variables		
law type	Whether common, as opposed to civil, law(*)	0.27	0.44
leniency	Whether leniency programme in place†	0.95	0.20
prosecutorial	Whether prosecutorial, as opposed to integrated, system(**)	0.36	0.48

Notes: †Global Competition Review Enforcement Report, ‡ Competition Authority Annual Reports, (*)[55], (**)[28]. + Cartels measures the number of cartels prosecuted by the CA, with the qualification that cartel decision cases do not include the number of cartels closed. ++Is the number of years a country has had a cartel law. For example, its value for the US in 2010 amounts to 120. This is because the Sherman Antitrust Act was passed in 1890.



(a) Worldwide (b) USA

Figure 1: Cartel counts over time (three-year moving average)

a worldwide phenomenon suggests that there may well be more than just US-specific explanations, such as shifts in policy regime, at work. However, a US-driven explanation cannot be ruled out, for example, if other countries around the world are encountering the same set of cartel cases, perhaps benefiting from the DoJ's detections. For these and other reasons, (e.g. the possibility that cartel age is endogenous) we remain cautious in how we interpret these results - we have detected an interesting descriptive fact, but one with more than one explanation. We return to the endogeneity issue in the next section.

Alongside the data on cartels, we have collated data from the web on single-firm conduct by the top digital platforms.[6] We have followed the following search rule. We searched the websites of the EU Competition Commission, the Department of Justice and the Federal Trade Commission, and the Competition and Markets Authority, and employed their case list search function, sorting by digital companies of interest. Following this, we conducted several searches of LexisLibrary, using the strings: “Abuse of Dominance”, “Single Firm Conduct Enforcement”, “Investigation” and “Monopolization”. We filtered the search results to search for each digital company of interest. Additionally, we conducted several high-level Google searches using the “Go Back in Time” application and searching for the aforementioned

easing. All these factors may have played a role in the rise of the quadratic function represented in the figure.

[6]We have only focused on antitrust decisions and not on consumer protection or tax avoidance decisions.

instructions. We searched using five-year intervals, back to the early eighties. We confined the search to the first three pages. Follow-up Google searches were then conducted to delve deeper into some of the information uncovered, for example, to follow up on any country-specific cases. The full list of the enforcement cases is documented in Table A1.

4 The evidence

Our main emphasis in this section is on the two areas of Antitrust, cartels and abuse of dominance. We note, very briefly, however, that there is increasing competition authority (CA) interest in Big Tech merger activity. Some recent empirical evidence of killer acquisitions in the pharmaceutical market ([20]),[7] and in innovative industries ([42]), together with the discussion of reverse-killer acquisitions by [8], and alongside some theoretical work by [26] and [27] have called for tighter merger policy (see, among others, [7] and [2]). The recent wave of acquisitions by Big Tech has raised concerns that merger controls are even more unfit for digital markets. Two influential competition policy reports [51] and [29] have voiced this concern to policymakers.

4.1 Antitrust (i) cartels

At the heart of cartel law and policy are formation and enforcement: one purpose is to deter and limit the rate at which cartels form, and the other purpose, if and when they do form, is to successfully enforce detection, prohibition, and penalties. The following framework aims to stylise, in a simple way, how these two effects interact to generate a profile of cartel detections over the lifetime of a competition authority. It shows that, under plausible assumptions, there will be an inverse-U-shaped profile, which can be explained in terms of the deterrence effect but also in terms of the degree of firm sophistication and monopolisation.

Suppose in the economy many markets, M, may be either cartelised or deterred from

[7] Defined by [20] as acquisitions that have the sole scope of shutting down the target's innovation project and eliminating future competition.

cartelising. Some of these markets, D, are deterred. Any undeterred cartel (the difference between the total number of markets and the deterred markets) is detected and successfully convicted (hereafter referred to simply as convicted) with a certain probability, τ. Deterrence is itself a function of this probability, $D(\tau)$, for the given number of markets. Deterrence is zero if the probability of detecting cartels is zero and it is the number of markets if the probability of convicting cartels is one. It is realistic to believe that deterrence increases with the probability of conviction, at a decreasing rate. When the probability is between zero and one, the expected number of convicted cartels, N, is a non-linear function of the probability of conviction due to the direct effect of the probability of conviction on the number of undeterred cartels and indirect, through its effect on deterrence, i.e., $N = \tau\,(M - D(\tau))$. This leads to the remark that the expected number of convicted cartels first increases with the conviction probability and falls thereafter.

The intuition is obvious: the higher the conviction probability, the greater the proportion of cartels convicted; but also, because deterrence grows stronger, fewer cartels are forming; eventually, greater deterrence will outweigh the increasing conviction rate.

To consider the intertemporal implications for the expected number of cartels convicted, we model how the probability of conviction varies over time. There are two broad alternatives. First, the probability of conviction increases monotonically over time at a declining rate. This situation is consistent with an increasing learning over time by the CA in its detection and convicting prowess. This gives rise to an inverse U-shaped time path in the number of cartels convicted by a CA. The second possibility is that after an initial learning phase, the probability of conviction reaches a maximum before falling back thereafter. This can be explained by strategic (and non-strategic) responses from the cartel or the competitive environment (for both reasons which we offer various explanations in the paper). Under certain conditions this generates (again) an inverse U-shaped time path; under others we observe multiple turning points, thus a polynomial of time of an order higher than two.[8]

[8] See [4] for the theory and proofs that justify the above claims.

To test this functional form with a panel model using the data described above, we can identify two parts to the hypothesis. First, there should be an inverse-U-shaped profile to the count of cartel cases. Second, that profile should be better captured using CA age as an explanatory variable rather than calendar time (to capture a worldwide exogenous explanation, e.g. the international business cycle), or the number of cartels detected in the USA, *uscartel* (to capture direct spillovers from US investigations of multinational cartels to other CAs). Of course, only the second part of the hypothesis can be tested because of the panel nature of the data, in which different CAs are at different stages in their evolution—this enables us to distinguish the impact of CA age from time alone.

The estimating equation of the number of cartels prohibited in country i and year t, with explanatory variables defined in Table 1, is:

$$\begin{aligned}\text{cartels}_{it} =& f(\text{age}_{it};\gamma) + \beta_0 + \beta_1 \ln \text{gnipi}_{it} + \beta_2 \text{leniency}_{it} + \beta_3 \ln \text{merger}_{it} + \beta_4 \ln \text{prison}_i + \\ &+ \beta_5 \text{law type}_i + \beta_6 \text{prosecutorial}_i + \mu_t + \nu_i + \varepsilon_{it}, \end{aligned} \tag{1}$$

where $f(\text{age}_{it};\gamma)$ is a polynomial of competition authority age and μ_t, and ν_i, are respectively time and Cartel Law unobserved heterogeneity. Given our interest in the age of Cartel Law, in our empirical analysis, we will account for the Cartel Law's unobserved heterogeneity using a random-effects approach.

Thus the hypothesis of an inverse-U against CA age will be tested through the polynomial, while the alternatives will be represented through μ_t, either in the form of *year* dummies or *uscartel*, the number of cartels in the US in year t. We experiment with two approaches to the polynomial: initially by fitting a simple quadratic on age, but then alternatively by fitting a fractional second-order polynomial.[9] While the standard quadratic form is the conventional

[9]Fractional polynomials differ from regular polynomials since they allow for both logarithms and non-integer powers. Powers can be repeated but, in this case, they are multiplied by some log power of the variable. For example, if the order of the polynomial is repeated m times, the fractional polynomial is $\gamma_0 + \gamma_1 x^p + \gamma_2 x^p \ln x + \gamma_3 x^p (\ln x)^2 + \cdots + \gamma_m x^p (\ln x)^{m-1}$. We use the Stata package `fp` [50]. The econometric procedure is a two-stage one. In the first stage, the optimal degree of the polynomial is chosen. The default in Stata is to select the power among the set of values $\{-2, -1, -0.5, 0, 0.5, 1, 2, 3\}$. The second stage is the

test for an inverse-U and helps to fix ideas, the fractional polynomial is preferred because it allows more flexibility in the exact shape of the inverse-U: the standard quadratic form imposes symmetry on the curve on either side of the turning point, the fractional polynomial allows the pre-peak growth and post-peak decline to differ in rapidity.

The error term ε_{it} is assumed to have a Negative Binomial distribution. Bearing in mind the count nature of cartels, the Negative Binomial or the Poisson are the obvious choices: in this case, we prefer the Negative Binomial because conventional tests reveal that the Poisson is inappropriate due to over-dispersion.[10]

We also include several other explanatory variables, each of which has featured prominently in previous economic and legal cartel works of literature, although here they largely fulfil a secondary control function ([3] provides longer discussions). Two, in particular, should control for potentially important confounding dynamic effects: *leniency* distinguishes between years in which the CA did or did not have recourse to a provision for leniency, and *mergers* is a count of the number of mergers referred to the competition authority, which will be an obligatory alternative demand on its resources. We include one other policy measure (*prison*, the maximum possible prison sentence), two indicators of the type of legal system in which the CA operates (*prosecutorial* and *law type*), and per capita gross national income *gnipi* is included as a control for a country's stage of development.

Columns (1) and (2) in Table 2 report the initial results when fitting a simple quadratic of cartel counts against the age of cartel law, and we test against the two alternative dynamic explanations: column (1) includes the vector of year dummy variables. At the 5% level, this provides significant evidence of an inverse-U: both age and age squared are significant and together they are jointly significant (p=0.05). This dominates the pure time effect, with only one of the year dummies significant, and taken together the vector of 12 dummies is insignificant at the 10% level. Second, column (2) replaces the year dummies with the count

regression of interest, given the optimal fractional polynomial. See [49] for a technical description of the estimator and [39] for an early application to electricity demand estimation.

[10] We use the `Stata` command `xtnbreg` with option random effects. This estimator is chosen also for the fractional polynomial regression.

of US cartels. Here, results are more mixed—the number of US cartels is just significant at the 5% level, and while the inverse-U against age is confirmed, its joint significance now slips to 7.8%.

Columns (3) and (4) repeat these two experiments, but now with a second-order fractional polynomial replacing the simple quadratic. Here, results are much more favourable to the inverse-U on age: the joint significance of age rises to 0.02 and 0.025 respectively and neither the year dummies in (3) nor US cartels in (4) are significant.[11] Given the flexibility of the fractional polynomial, we choose this as the preferred methodology; and, as a test of robustness, Column (5) adds six control variables to column (4), and this confirms that the significance of the polynomial and the insignificance of US cartels are robust to the inclusion of these additional regressors. The only one of the covariates to be significant is *leniency*—more cases are detected in jurisdiction-years in which there is a leniency programme. [12]

Based on these results, both parts of the key remark can be accepted: as shown in Figure 3, there is indeed an inverse-U shape to the profile of cartel detections, and the best fit is achieved by using the age of the CA rather than mere time alone. From the estimated coefficients of the equations, the turning point, the CA age at which cartel detections are at a peak lies somewhere in the range of 60-67 years. This is well within the sample range of observations, one-third of the CAs have age greater than that range at some point in the sample period.

Our data description and empirical analysis document key associations in the data. Our data are not rich enough to attribute a causal effect or mechanism of age and the number of cartels convicted. Cartel age depends on the passing of the cartel law, which is not exogenous.

[11]For the polynomial of order two, the functional form that best fits the data is $f = \gamma_1 age^3 + \gamma_2 age^3 \times \ln(age)$; this function has a maximum at age $= \exp\left(-\frac{3\gamma_1+\gamma_2}{3\gamma_2}\right)$.

[12]The bottom panel of the table displays some statistics of a polynomial of order three. The significance of the regressions documented in columns (1) and (2) worsens relative to that of the polynomial of order two, improving marginally for the fractional version, shifting in this latter case, the peak of age slightly on the right. The shape of the function remains inverse-U shape. For this reason, our focus remains on the quadratic polynomial as it is more conservative and conveys the same message.

Table 2: Regression results for cartels

	(1)	(2)	(3)	(4)	(5)
	quadratic		fractional polynomial†		
age/100 order 1	3.073^c	2.698^c	-1.014	-0.948	-1.041
	(1.333)	(1.288)	(0.643)	(0.621)	(0.612)
age/100 order 2	-2.811^c	-2.483	-7.074^b	-6.627^b	-6.315^c
	(1.425)	(1.390)	(2.550)	(2.470)	(2.473)
ln gnipc					-0.202
					(0.141)
leniency					0.587^c
					(0.264)
ln merger					0.066
					(0.048)
ln prison					-0.027
					(0.082)
law type					-0.354
					(0.216)
prosecutorial					-0.019
					(0.198)
US cartel		0.003^c		0.003	0.002
		(0.002)		(0.002)	(0.002)
cons	0.014	0.028	0.361	0.347^c	1.735
	(0.295)	(0.282)	(0.194)	(0.160)	(1.502)
ln r	1.287^a	1.287^a	1.284^a	1.283^a	1.459^a
	(0.275)	(0.276)	(0.275)	(0.276)	(0.313)
ln s	2.276^a	2.326^a	2.267^a	2.314^a	2.524^a
	(0.308)	(0.309)	(0.308)	(0.309)	(0.361)
N	382	382	382	382	381‡
			Polynomial order two		
p-val regression	0.074	0.045	0.046	0.016	0.010
p-val age/100	0.050	0.078	0.020	0.025	0.038
p-val time dummies	0.111		0.129		
arg max	54.65^a	54.33^a	62.09^a	62.10^a	60.77^a
			Polynomial order three		
p-val regression	0.081	0.053	0.044	0.015	0.011
p-val age/100	0.073	0.089	0.022	0.021	0.043
p-val time dummies	0.130		0.174		
arg min	4.29	8.69	23.51^c	24.78^b	25.05^c
arg max	60.15^a	60.83^a	66.97^a	67.52^a	66.44^a

Notes: Year dummies are included. ^{c}p<0.05, ^{b}p<0.01, ^{a}p<0.001. †Polynomial of order 1 is (age^3); polynomial of order 2 is $(age^3 \times \ln age)$. ‡We lose one observation because there were zero mergers in Chile in 2013. The value of ln merger is missing for that country and year.

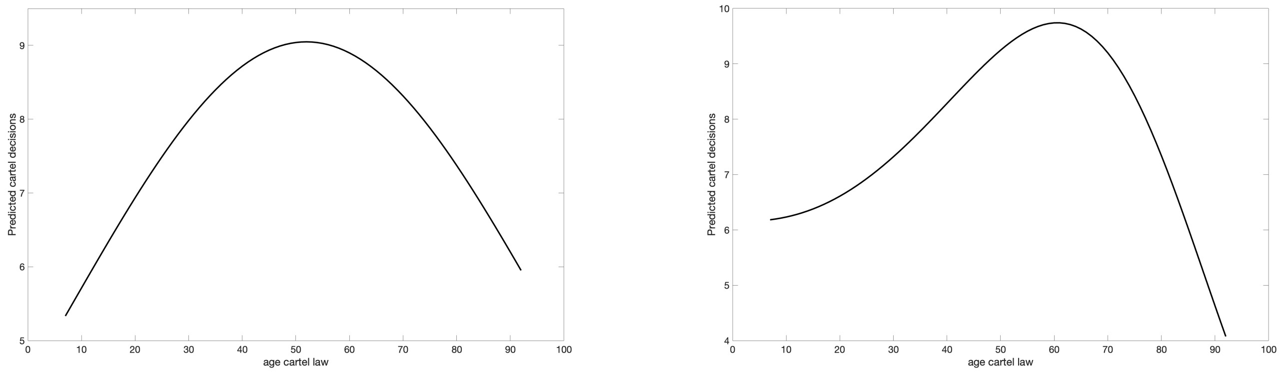
Neither exogenous is the learning that correlates the age of cartel law with the number of cartels convicted. The globalisation of competition law enforcement and convergence of competition regimes facilitate the learning process, and so do the many competition-policy networks.[13] These networks also contribute to the application of transnational competition laws. With them, cartel decisions (our cartel count) spill over to various countries. There is then the factor that, at times, cartels are transnational. Thus, once convicted in a country, they can be charged in other countries. In our empirical analysis, we account for the type of law and US cartel decisions, as US cartel decisions generate strong spillovers (see [1] for an analysis that accounts for the US cartel decisions on EU cartel decisions). We cluster the standard errors over firms but do not deal with spatial correlation as this is complicated, and not captured by geographical proximity. Ours, are attempts to mitigate important omitted variables that we believe can contribute to spillovers. An instrumental variables approach would need to have availability of variables correlated with the year of the cartel law and/or the latent learning curve while uncorrelated with the number of cartel decisions, if not via the age of cartel law. Such data are hard to find. Our dataset was not rich enough to achieve this.

4.2 Antitrust, (ii) single-firm conduct

For this part of the analysis, we use the information that we have collected from the web on several enforcement decisions or ongoing decisions by competition authorities around the world. In recent years more and more CAs have reformed their regulations (Digital Markets Act in the EU and Digital Market Unit in the UK) or provided detailed studies in markets where these top tech companies operate. Part of these regulation changes is described in the report [43].

As explained in the Data Section, we searched for abuse of dominance cases brought

[13]To mention a few of the competition networks, we have the International Competition Network (ICN), OECD Competition Committee, UNCTAD Intergovernmental Group, and ASEAN Expert Group on Competition (consult [44] for a more comprehensive list).



(a) Simple quadratic

(b) Fractional polynomial of order two

Figure 2: Predicted cartel counts over the CA lifecycle

against the five big digital firms. Table A1 lists the various entries that we managed to find. The list includes cases that have received wide media attention. To mention a few, the EU competition agency accused Google of infringement of antitrust law for discouraging smartphone device manufacturers from adopting competing operating systems and requiring producers to install Chrome and set Google as the default search engine. In 2017, The EU Competition Commission raised concerns about Amazon's practice of asking its e-book suppliers for notification of any Most Favoured Nation conditions offered to other retailers. Retrospectively, 2020, The FTC sued Facebook for their mergers with Instagram consummated in 2011 and WhatsApp in 2014, as these were recognised as potential challengers to Facebook's dominant position in the market. Relatively to the Facebook-WhatsApp merger, the EU Competition Commission fined Facebook for providing misleading information during its investigation of the acquisition.

From the dataset on the abuse of dominant positions by GAFAM firms that we collated, we construct the variable number of abuses per year based on the year the case was opened (see list of cases on Table A1, column (1)) and plot in Figure 3, the moving average of order three of this count variable. We observe a sizeable switch in the way competition authorities around the world interpret some of the behaviour by the Big Tech firms, showing a structural change in enforcement starting from 2019 and possibly continuing in subsequent years until deterrence and sophistication kick in this part of the Antitrust.

Part of the explanation for this exponential growth in the number of abuse of dominant positions investigated by competition authorities is the diffusion of proposals for regulatory reforms. Many jurisdictions, including the EU and the UK, have published their proposal for regulatory reforms in the digital market. The EC published in 2020 its draft for the Digital Market Act (DMA) and Digital Services Act (DSA). Altogether these proposals for regulating the market have put pressure on investigations by national CAs (see discussion in [43]), and some of these authorities have created specialised digital units.

For the overlapping period 2006-2018, there is a significantly negative Pearson correlation coefficient (-0.714) between the moving average of order three of abuse of dominant positions by GAFAM firms and the same moving average for the number of cartel cases detected by an average. This can be seen as suggestive evidence of displacement of cartelisation by anticompetitive behaviour driven by the process of monopolisation, at least for data on the dominant GAFAM firms.

Finally and for completeness, although digital platforms have been investigated mainly for abuse of dominant positions, there are a handful of instances where they are under investigation or being convicted for being part of secret collusive agreements. We itemise various cases in Table A2. The top panel lists more classic forms of horizontal agreements which involved one or more GAFAM firms. The bottom panel lists collusive agreements that are either vertical features or occur on the platforms. These agreements are not always deliberate, but yet, they may end up featuring collusive features and price-fixing. That was the case for the Apple e-book price-fixing case. Apple wanted to compete with Amazon and thus moved away from the wholesale model adopted by Amazon towards an agency model. The US Second Circuit Court found Apple guilty of facilitating price-fixing when they sat at the table with five book publishers to discuss pricing.

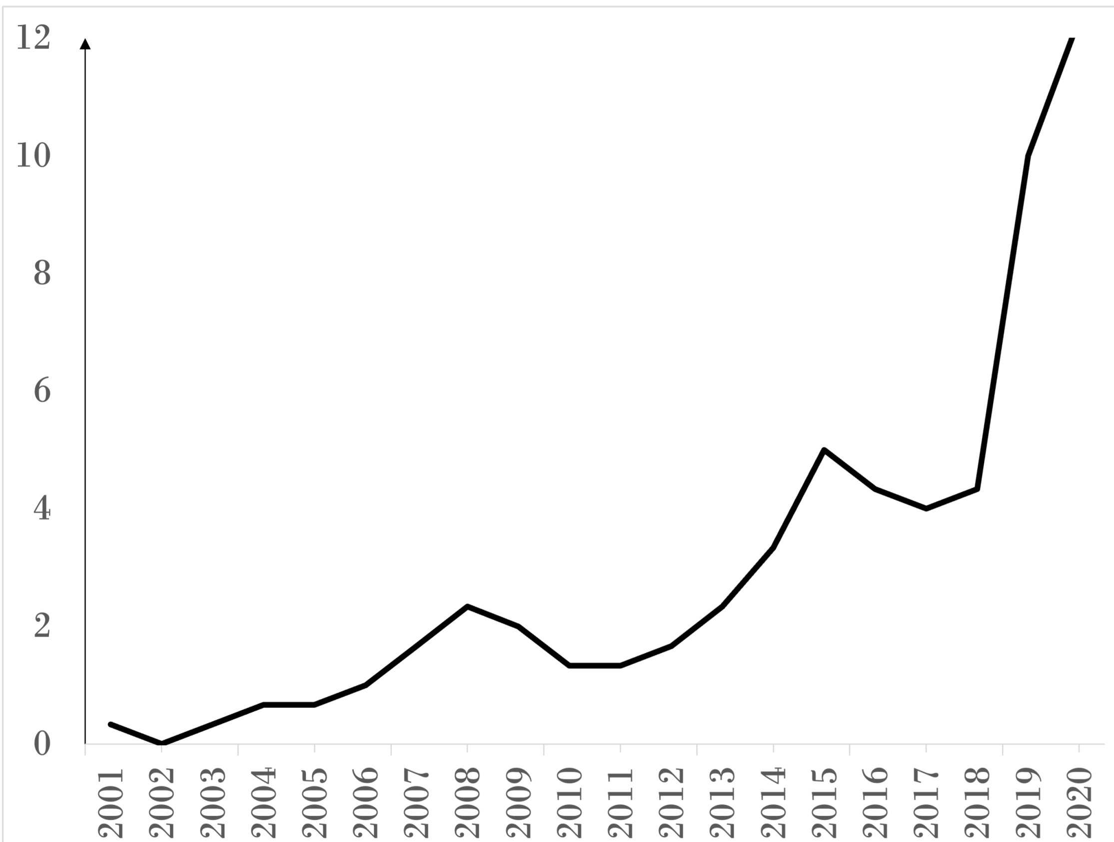


Figure 3: GAFAM cases of single-firm conduct over time (three-year moving average)

5 Discussion and conclusions

This paper began by recalling two of the key propositions of "Monopoly Capitalism" [19]: the norm in an increasingly oligopolistic world will be collusion, and the largest corporations have captured dominant positions which are relatively unassailable.

Evidence from recent bodies of literature offers some support, but only some. On the one hand, as described in the literature review section, evidence is accumulating that concentration has been increasing worldwide since the turn of the century. On the other hand, however, there is some evidence for the USA, of declining cartel activity (at least as measured by the number of cartels detected and prosecuted.)

The first objective of this paper was to establish empirically whether the downturn in detected cartels was a worldwide phenomenon. Based on a panel database of 32 CAs from around the world, it finds that the downturn is indeed worldwide. Since this reverses the worldwide trend of increasing cartel detections in previous years, we refer to this as the "inverse U". As a descriptive fact, this formalises what had previously been piecemeal evidence for the USA and importantly generalises the inverse U to the rest of the world.

We have discussed three alternative explanations for this inverse-U. The first is that it merely reflects some worldwide trend which has had a common effect across all countries equally. While the causes of such a trend might be related to, say, the financial crisis or more generally the worldwide business cycle, we did not restrict our test of this hypothesis which was non-parametric, merely involving year dummy variables. The second potential explanation is that the US Competition Authority (DoJ) plays a dominant role in worldwide cartel enforcement—in discovering and prosecuting, particularly multinational cartels. So such cases, once prosecuted in the USA, can be more easily prosecuted by competition authorities (CAs) from other jurisdictions. Like the first hypothesis, this implies parallel time profiles across countries, but in this case, more specifically tied to the pattern of US enforcement. The third hypothesis is that the inverse-U is the consequence of some increasingly strong countervailing force that impacts negatively on the number of cases detected in a given CA over its life cycle. We offer two suggestions on what this countervailing force might be. The problem is that they have contradictory implications for the success of the cartel policy. Is it that cartel policy might be failing—mirroring (some would say) contemporary evidence that merger policy is increasingly ineffective? For example, with time, CAs are resting on their laurels, gradually becoming less proficient at detection. Or, what comes to the same thing, is it that the cartelists themselves become increasingly adept at concealing their conspiracies as their experience grows? This line of thinking would not necessarily undermine Cowling's suggestion of increasing collusion, the cartels are still there, but no longer being detected. But the alternative explanation of the inverse U is much more favourable to the CAs: the countervailing force is deterrence and the successes of cartel policy are increasingly effective at dissuading cartels from forming in the first place. This is less supportive of the Cowling prediction but, rather, advocates the view that cartel policy has succeeded in turning the tide of collusion.

The second objective of the paper was to explore the role of Big Tech firms in this story. Of course, Big Tech had yet to emerge 40 years ago, and an obvious question to ask now is whether the emergence of GAFAM has undermined Cowling's vision of monopoly capitalism. Here, one feature of the cartel data is immediately and strikingly apparent: these firms rarely if ever engage in horizontal cartels (although the existence of platforms arguably facilitates within-platform collusion, i.e. between firms using the platforms.) However, this does not mean that GAFAM have steered clear of alleged anti-competitive behaviour. On the contrary, the second database we have assembled reveals a very different story. In this case, the data refer, not to collusion, but, rather, the other arm of competition law: single-firm behaviour, referred to variously as monopolisation or abuse of dominance cases. Even confining this to the five GAFAM firms, our data reveal an exponential explosion of cases brought against the firms worldwide.

Another potential role for the Big Tech firms which might yet support Cowling's suggestion of ever-increasing collusion is in facilitating tacit collusion, in terms of increasing price transparency on platforms and helping introduce algorithmic pricing which is conducive to softening of price competition.

With the evidence currently at our disposal, this current paper cannot conclusively discriminate between competing interpretations, and further work is necessary. However, given that this paper belongs to a Special Issue in honour of Keith Cowling, a natural way to conclude is to speculate on how Keith would have reacted to the portfolio of facts we have assembled. Some developments over recent decades are exactly as he would have predicted —most obviously: increasing concentration, increasing markups and the emergence of a handful of dominant giant firms. The increases in monopoly abuse cases by those firms can also be interpreted as evidence of strategic behaviour designed to deter potential competition.

The one fact that superficially contradicts Cowling's vision is the apparent tailing off in cartel cases, both in the USA and worldwide. However, even this contradiction might be offset by remembering that collusion can take many forms, of which the hard core cartel is only one. Another form, frequently discussed by Cowling, is tacit collusion, where the fear of retaliation from rivals deters firms from pricing aggressively. So fears of 'tit-for-tat' rivalry (à la Akerloff) lead to the absence of effective competition. Another form of collusion, much discussed in the early days of Structure-Conduct-Performance is "mutual forbearance" —this occurs when potentially a group of large firms, each dominant in their own product/geographic space, deliberately back off from entering into their potential rivals' home territories. Again, paradoxically, the effect of this sort of collusion is the absence of any credible competitors in a given market.[14][15]

[14] This is, of course, extremely difficult to prove or verify. For example, proof of such territorial exclusivity agreements is sufficient grounds for prosecution when enacted within cartels; but very few such cases are ever actually prosecuted given the intangible nature of the phenomenon.

[15] The key question is whether GAFAM firms can provide a competitive constraint on each other's behaviour. ([47]) defines a new form of competition, labelled "moligopoly", by which large companies compete with one another across markets, including nearby markets, but not within the core markets they dominate. ([25]) details the large number of cases where the GAFAM firms offer competing products. In many instances, these product offerings are marginal, and even where there is competition it is a duopoly, potentially with a dominant firm On the other hand, it is erroneous to think that dominant players face no competitive threat. For example, Evans reports Bing vs Google in search, Chrome vs Safari vs Edge in browsers, Gmail vs Outlook in email, WhatsApp vs FaceTime vs Skype for video calls, and Siri vs Alexa in voice assistants.

At this stage, to go any further, we can only look to the future. If GAFAM have all passed their tipping points, does this mean that they are safe from Schumpeterian creative destruction over the long term? If so, will there be persistence of dominance in the long run? Or will new rivalries emerge from new firms and technologies, and how will this impact the incentives to collude and in what form?

In the appendix, Table A3 we provide some simple data, derived from S&P, which reveals strikingly how rapidly GAFAM have become the giants of the world economy. It remains to be seen how if at all, this will change over the coming decade.

References

[1] , Aguzzoni, Luca and Langus, Gregor and Motta, Massimo, “The effect of EU antitrust investigations and fines on a firm’s valuation”, The Journal of Industrial Economics, 61-2, pp.290-338, 2013, `https://doi.org/10.1111/joie.12016`.

[2] Argentesi, Elena and Buccirossi, Paolo and Calvano, Emilio and Duso, Tomaso and Marrazzo, Alessia and Nava, Salvatore, “Merger policy in digital markets: An ex post assessment”, Journal of Competition Law & Economics, 17-1, pp.95-140, 2021, `https://doi.org/10.1093/joclec/nhaa020`.

[3] Armoogum, Prishnee K., “Assessing the comparative performance of competition authorities”, PhD thesis, University of East Anglia, 2016.

[4] Armoogum, Prishnee and Davies, Stephen and Mariuzzo, Franco, “Is Cartel enforcement declining worldwide, and, if so, why?”, Centre for Competition Policy and School of Economics, University of East Anglia CCP Working Paper, 17-4 (v02), 2017.

[5] Dorn, David and Katz, Lawrence F and Patterson, Christina and Van Reenen, John and others, “Concentrating on the Fall of the Labor Share”, American Economic Review, 107-5, pp.180-85, 2017, `https://doi.org/10.1257/aer.p20171102`.

[6] Autor, David and Dorn, David and Katz, Lawrence F. and Patterson, Christina and Van Reenen, John, "The fall of the labor share and the rise of superstar firms", The Quarterly Journal of Economics, 135-2, pp.645-709, 2020, https://doi.org/10.1093/qje/qjaa004.

[7] Berry, Steven and Gaynor, Martin and Scott Morton, Fiona M., "Do increasing markups matter? Lessons from empirical industrial organization", Journal of Economic Perspectives, 33-3, pp.44-68, 2019, https://doi.org/10.1257/jep.33.3.44.

[8] Caffarra, Cristina and Crawford, Gregory S. and Valletti, Tommaso, "How tech rolls: Potential competition and "reverse" killer acquisitions", Antitrust Chronicle, 2-2, pp.1-9, 2020.

[9] Calvano, Emilio and Calzolari, Giacomo and Denicolo, Vincenzo and Pastorello, Sergio, "Artificial intelligence, algorithmic pricing, and collusion", American Economic Review, 110-10, pp.3267-97, 2020, https://doi.org/10.1257/aer.20190623.

[10] Calvano, Emilio and Calzolari, Giacomo and Denicolò, Vincenzo and Pastorello, Sergio, "Algorithmic pricing what implications for competition policy?", Review of Industrial Organization, 55-1, pp.155-171, 2019, https://doi.org/10.1007/s11151-019-09689-3.

[11] Capobianco, Antonio and Gonzaga, Pedro, "Algorithms and competition: Friends or foes?", Competition Policy International, 1, p.2, 2017.

[12] Competition and Markets Authority, "The State of UK Competition", CMA 133 https://tinyurl.com/n22hdmxx (accessed 10-Aug-2022), 2020.

[13] Connor, John M, "Comment on cartel enforcement in the Trump administration", CPI Antitrust Chronicle June, 2019.

[14] Council of Economic Advisers, “Benefits of competition and indicators of market power”, The Government Report, 2016.

[15] Covarrubias, Matias and Gutiérrez, German and Philippon, Thomas, “From good to bad concentration? US industries over the past 30 years”, NBER Macroeconomics Annual, 34, eds. M S Eichenbaum, Hurst E and J Parker, 2019, https://doi.org/10.3386/w25983.

[16] Cowling, Keith and Waterson, Michael, “Price-cost margins and market structure”, Economica, 43, pp.267-260, 1976, https://doi.org/10.2307/2553125.

[17] Cowling, Keith and Cable, John and Kelly, Mike and McGuinness, Tony, “Advertising and Economic Behavior”, The Macmillan Press, Ltd., London, 1975.

[18] Cowling, Keith, “Oligopoly, distribution and the rate of profit”, European Economic Review, 15-2, pp.195-224, 1981, https://doi.org/10.1016/0014-2921(81)90087-8.

[19] Cowling, Keith, “Monopoly capitalism”, Macmillan International Higher Education, 1982., https://doi.org/10.1007/978-1-349-16681-7.

[20] Cunningham, Colleen and Ederer, Florian and Ma, Song, “Killer acquisitions”, Journal of Political Economy, 129-3, pp.649-702, 2021, https://doi.org/10.1086/712506.

[21] Davies, Stephen, “Competition and concentration: Charting the faultlines”, CCP Working Paper 21-11, University of East Anglia, 2021.

[22] De Loecker, Jan and Eeckhout, Jan, “Global market power”, National Bureau of Economic Research, 2018, https://doi.org/10.3386/w24768.

[23] De Loecker, Jan and Eeckhout, Jan and Unger, Gabriel, “The rise of market power and the macroeconomic implications”, The Quarterly Journal of Economics, 135-2, pp.561-644, 2020, https://doi.org/10.1093/qje/qjz041.

[24] Dorn, David and Katz, Lawrence F. and Patterson, Christina and Van Reenen, John, "Concentrating on the fall of the labor share", American Economic Review, 107-5, pp.180-85, 2017, https://doi.org/10.1257/aer.p20171102.

[25] Evans, David S, "Why the dynamics of competition for online platforms leads to sleepless nights but not sleepy monopolies", SSRN 3009438, 2017, https://doi.org/10.2139/ssrn.3009438.

[26] Federico, Giulio and Langus, Gregor and Valletti, Tommaso, "A simple model of mergers and innovation", Economics Letters, 157, pp.136-140, 2017, https://doi.org/10.1016/j.econlet.2017.06.014.

[27] Federico, Giulio and Langus, Gregor and Valletti, Tommaso, "Reprint of: Horizontal mergers and product innovation", International Journal of Industrial Organization, 61, pp.590-612, 2018, https://doi.org/10.1016/j.ijindorg.2018.11.005.

[28] Fox, Eleanor M and Trebilcock, Michael J, "The design of competition law institutions: global norms, local choices", Oxford University Press, 2012.

[29] Furman, Jason and Coyle, Diane and Fletcher, Amelia and McAuley, Derek and Marsden, Philip, "Unlocking digital competition. Report of the Digital Competition Expert Panel", OGL, 2019.

[30] Furman, Jason and Orszag, Peter R, "Slower productivity and higher inequality: Are they related?", Peterson Institute for International Economics Working Paper, 2018, https://doi.org/10.2139/ssrn.3191984.

[31] Garside, Ludivine and Grout, Paul A., and Zalewska, Anna, "Does experience make you 'tougher'? Evidence from competition law", The Economic Journal, 123-568, pp.474-490, 2013, https://doi.org/10.1111/j.1468-0297.2012.02560.

[32] Ghosal, Vivek and Sokol, D Daniel, “The evolution of US cartel enforcement”, “The Journal of Law and Economics”, 57-S3, pp.S51-S65, 2014, https://doi.org/10.1086/676070.

[33] Ghosal, Vivek and Sokol, Daniel D., “The rise and (potential) fall of US cartel enforcement”, University of Illinois Law Review, pp.471-508, 2020.

[34] Grullon, Gustavo and Larkin, Yelena and Michaely, Ron, “Are US industries becoming more concentrated?”, Review of Finance, 23-4, pp. 697-743, 2019, https://doi.org/10.1093/rof/rfz007.

[35] Gutiérrez, Germán and Philippon, Thomas, “Declining Competition and Investment in the US”, NBER, w23583, 2017, https://doi.org/10.3386/w23583.

[36] Gutiérrez, Germán and Philippon, Thomas, “How European markets became free: A study of institutional drift”, NBER, w24700, 2018, https://doi.org/10.3386/w24700.

[37] Hansen, Karsten T. and Misra, Kanishka and Pai, Mallesh M., “Frontiers: Algorithmic collusion: Supra-competitive prices via independent algorithms”, Marketing Science, 40-1, pp.1-12, 2021, https://doi.org/10.1287/mksc.2020.1276.

[38] Harrington, Joseph E., “Developing competition law for collusion by autonomous artificial agents”, Journal of Competition Law & Economics, 14-3, pp.331-363, 2018, https://doi.org/10.1093/joclec/nhy016.

[39] Henley, Andrew and Peirson, John, “Non-linearities in electricity demand and temperature: parametric versus non-parametric methods”, Oxford Bulletin of Economics and Statistics, 59-1, pp.149-162, 1997, https://doi.org/10.1111/1468-0084.00054.

[40] Kühn, Kai-Uwe and Tadelis, Steve, “Algorithmic collusion”, Presentation prepared for CRESSE, https://tinyurl.com/yc8akzck (accessed 10-Aug-2022), 2017.

[41] Kwoka, John, “Controlling mergers and market power: A program for reviving antitrust in America”, CPI Books, 2020.

[42] Igami, Mitsuru and Uetake, Kosuke, “Mergers, innovation, and entry-exit dynamics: Consolidation of the hard disk drive industry, 1996–2016”, The Review of Economic Studies, 87-6, pp.2672-2702, 2020, `https://doi.org/10.1093/restud/rdz044`.

[43] Mansfield, Philip and Masterman, Thomas and Carr, Imogen and Piddington, Rachael, “Global antitrust enforcement report”, Allen & Overy, 2021.

[44] Maher, Imelda and Papadopoulos, Anestis, “Competition agency networks around the world”, in Research Handbook on International Competition Law, Edward Elgar Publishing, 2012, `https://doi.org/10.4337/9780857934802.00011`.

[45] Miklós-Thal, Jeanine and Tucker, Catherine, “Collusion by algorithm: Does better demand prediction facilitate coordination between sellers?”, Management Science, 65-4, pp.1552-1561, 2019, `https://doi.org/10.1287/mnsc.2019.3287`.

[46] OECD, “OECD competition trends”, 2020.

[47] Petit, Nicolas, “Big tech and the digital economy: The moligopoly scenario”, Oxford University Press, 2020, `https://doi.org/10.1093/oso/9780198837701.001.0001`.

[48] Philippon, Thomas, “The great reversal: How America gave up on free markets”, Harvard University Press, 2019, `https://doi.org/10.4159/9780674243095`.

[49] Royston, Patrick and Altman, Douglas G., “Regression using fractional polynomials of continuous covariates: parsimonious parametric modelling”, Journal of the Royal Statistical Society: Series C (Applied Statistics), 43-3, pp.429-453, 1994, `https://doi.org/10.2307/2986270`.

[50] Royston, Patrick and Altman, Douglas G,“Using fractional polynomials to model curved regression relationships”, Stata Technical Bulletin, 4-21, 1995.

[51] Scott-Morton, Fiona and Bouvier, Pascal and Ezrachi, Ariel and Jullien, Bruno and Katz, Roberta and Kimmelman, Gene and Melamed, Douglas and Morgenstern, Jamie, "Stigler committee on digital platforms", Stigler Center for the Study of the Economy and the State, Chicago Booth, 2019.

[52] Shapiro, Carl, "Protecting competition in the American economy: Merger control, tech titans, labor markets", Journal of Economic Perspectives, 33-3, pp.69-93, 2019, https://doi.org/10.1257/jep.33.3.69.

[53] Shapiro, Carl, "Antitrust in a time of populism", International Journal of Industrial Organization, 61, pp.714-748, 2018, https://doi.org/10.1016/j.ijindorg.2018.01.001.

[54] Simcha, Barkai, "Declining labor and capital shares", Journal of Finance, 75-5, pp.2421-2463, 2020, https://doi.org/10.1111/jofi.12909.

[55] Tetley, William, "Mixed Jurisdictions: Common Law v. Civil Law (Codified and Uncodified)", Lousiana Law Review, 60, p.677, 1999, https://doi.org/10.1093/ulr/4.4.877.

[56] The Economist, "Too much of a good thing. Profits are too high. America needs a giant dose of competition", The Economist, May 26 2016.

[57] White House Council of Economic Advisers, "Benefits of competition and indicators of market power", https://tinyurl.com/5dwre765 (accessed 10-Aug-2022), 2016.

Table A1: Cases of single-firm conduct by GAFAM firms

Year Opened	Year Closed	Closed/Open	Fine Y/N	Fine Amount	Company	Authority
2010	2017	Closed	Y	2.42bn Euros	Alphabet/Google	European Commission
2015	2018	Closed	Y	4.34bn Euros	Alphabet/Google	European Commission
2016	2019	Closed	Y	1.49bn Euros	Alphabet/Google	European Commission
2013	2013	Closed	N - order imposed		Alphabet/Google	Federal Trade Commission (USA)
2020		Open			Alphabet/Google	Department of Justice (USA)
2011	2011	Closed	N - order imposed		Alphabet/Google	Department of Justice (USA)
2015	2016	Closed	Y	1-15% of revenue on 2014 Russian market	Alphabet/Google	FAS (Russia)
2020		Open			Alphabet/Google	Competition Appeal Tribunal (UK)
2020	2021	Closed	Y	36.65m US dollars	Alphabet/Google	Turkey Competition Board
2021	2022	Closed	N-accepted commitments		Alphabet/Google	Competition and Markets Authority (UK)
2020	2021	Closed	Y	102.8m Euros	Alphabet/Google	Italian Competition Authority
2019	2020	Closed	Y	25.74m US dollars	Alphabet/Google	Turkey Competition Board
2015	2018	Closed	Y	15m US dollars	Alphabet/Google	Turkey Competition Board
2014	2015	Closed	N		Alphabet/Google	German Bundeskartellamt
2019	2020	Closed	N-Precautionary measures link		Alphabet/Google	French Competition Authority
2014	2015	Closed	N	Commitments	Alphabet/Google	AGCM (Italy)
2021	2021	Closed	Y	Up to 500m Euros	Alphabet/Google	French Competition Authority
2021	2022	Closed	N		Alphabet/Google	German Bundeskartellamt
2020		Open			Amazon	European Commission
2019		Open			Amazon	European Commission
2015	2017	Closed	N - accepted commitments		Amazon	European Commission
2012	2013	Closed	N		Amazon	Competition and Markets Authority (UK)
2019	2020	Closed	N		Amazon	Competition Commission of India
2019	2020	?			Amazon	Italian Competition Authority
2018	2019	Closed	N - adjustment of terms		Amazon	German Bundeskartellamt
2020		Open			Amazon	German Bundeskartellamt
2020		Open			Amazon	German Bundeskartellamt
2014	2015	Closed	N	Commitments	Amazon	AGCM (Italy)
2021		Open			Amazon	Spanish Competition Authority
2021		Open			Amazon	German Bundeskartellamt
2020		Open			Amazon	Canadian Competition Bureau
2016	2017	Closed	Y	1m CAD	Amazon	Canadian Competition Bureau
2020		Open			Apple	German Bundeskartellamt
2021		Open			Apple	German Bundeskartellamt
2020		Open			Apple	European Commission
2020		Open			Apple	European Commission
2020		Open			Apple	European Commission
2020		Open			Apple	European Commission
2007	2008	Closed	N		Apple	European Commission
2013	2015	Closed	N - order imposed		Apple	Department of Justice (USA)
2018	2019	Closed	N		Apple	Supreme Court (USA)
2020	2021	Closed	Y	12m US dollars	Apple	FAS (Russia)
2016	2017	Closed	N - order imposed		Apple	FAS (Russia)
2016	2017	Closed	Y	16-18,000 Euros	Apple	FAS (Russia)
2020		Open			Apple	Competition Appeal Tribunal (UK)
2019	2021	Closed	Y	5m euros per week, up to a maximum of 50m euros.	Apple	Netherlands Authority for Consumers and Markets
2021		Open			Apple	Competition and Markets Authority (UK)
2019	2020	Closed	y	1.1 Billion euros	Apple	French Competition Authority
2009	2010	Closed	N	Commitments - will stop the practice	Apple	French Competition Authority
2021		Open			Apple	Spanish Competition Authority
2021		Open			Apple	German Bundeskartellamt
2020		Open			Facebook	Federal Trade Commission (USA)
2020	2020	Closed	N - order imposed		Facebook	Federal Supreme Court of Germany
2019	2020	Closed	N		Facebook	Competition Commission of India
2018	2019	Closed	N	Prohibition	Facebook	German Bundeskartellamt
2020		Open	N		Facebook	German Bundeskartellamt
2021		Open			Facebook	European Commision
2018	2018	Closed	Y	10m Euros	Facebook	AGCM (Italy)
2016	2018	Closed	Y	3mn Euros	Facebook	AGCM (Italy)
2016	2017	Closed	Y	1.2m Euros	Facebook	Spanish Competition Authority
2021		Open			Facebook	German Bundeskartellamt
2016		Open			Facebook	Polish Competition Authority
2000	2004	Closed	Y	497m Euros	Microsoft	European Commission
2005	2006	Closed	Y	280.5m Euros	Microsoft	European Commission
2007	2008	Closed	Y	899m Euros	Microsoft	European Commission
2009	2010	Closed	N		Microsoft	European Commission
2015	2016	Closed	N		Microsoft	European Commission
2008	2009	Closed	N - accepted commitments		Microsoft	European Commission
2012	2013	Closed	Y	561m Euros	Microsoft	European Commission
2008	2016	Closed	N		Microsoft	European Commission
2017	2019	Closed	N - accepted commitments		Microsoft	FAS (Russia)
2004	2005	Closed	Y	32m US dollars	Microsoft	Korea Fair Trade Commission
2008	2009	Closed	N		Microsoft	Seoul district court
1998	2001	Closed		Fines not determined from this - determined in 2004 case	Microsoft	United States Department of Justice (DoJ)

Table A2: GAFAM cartel cases and cartel cases in their platforms

Firms involved	Description
	Cartel cases by GAFAM firms
Google, Facebook, & Twitter	(2018) Firms banned cryptocurrency advertising in 2018 within weeks of each other. (Australian class action https://www.dailymail.co.uk/news/article-8444385/Google-Facebook-Twitter-sued-Australian-class-action-cost-300-billion.html).) (Horizontal cartel.)
Apple & Google	(2021) Google paid Apple to 'stay out' of search engine business, Google to share profits with Apple from search ads (US class action https://www.docketalarm.com/cases/California_Northern_District_Court/3--21-cv-10001/California_Crane_School_Inc._v._Google_LLC__et_al/1) (Horizontal cartel.)
Google & Facebook	(2021) Jedi Blue: Collusion between firms to rig the online ad market in their favour and the integration of systems so that Google can pass data to Facebook for user ID cookie matching (Attorneys various US states).(https://www.documentcloud.org/documents/21179902-3rd-complaint-for-texas-google-antitrust-case) (European Commission and The CMA https://www.reuters.com/technology/eu-opens-google-facebook-advertising-deal-investigation-2022-03-11/) (Horizontal cartel.)
Amazon & Apple	(2020) "Competing ads removed from search" results on Amazon (FTC investigation https://www.reuters.com/article/us-apple-amazon/favorable-ad-search-terms-for-apple-considered-in-deal-with-amazon-documents-idUSKCN24V06K) (Horizontal cartel.)
Amazon & Apple	(2021) Alleged collusion of Apple and Beats kit on Amazon's Italian e-commerce marketplace. (Italian Competition Authority https://en.agcm.it/en/media/press-releases/2021/12/I842) (Horizontal cartel.)
Apple, Google, Intel, & Adobe	(2014) Allegations of firms conspiring to keep wages low in Silicon Valley and to avoid hiring from within each others' ranks. (US Department of Justice https://www.vanityfair.com/news/business/2014/04/apple-google-settle-wage-fixing-hiring-case) (Horizontal cartel.)
Amazon & Apple	(2020) Exclusion of non-authorised dealers from selling Apple products on the Amazon Marketplace. (Bundeskartellamt https://www.clearygottlieb.com/-/media/files/german-competition-law-newsletters/german-competition-newsletter-nov-dec-2020.pdf) (Federal Trade Commission) (https://www.theverge.com/2019/8/2/20751482/ftc-amazon-apple-iphone-reseller-agreement-antitrust) (Horizontal cartel.)
	Cartel cases in GAFAM platforms
Apple	(2020) Apple and its two wholesalers (Tech Data and Ingram Micro) agreed not to compete with each other and to prevent distributors from competing with each other (French Competition Authority https://news.sky.com/story/apple-fined-1-2bn-after-french-price-fixing-probe-11958480) (Horizontal cartel.)
Apple	(2017) Apple instructed numerous sellers to set prices at a certain level, and subsequently contacted those that didn't comply to request they reconsider (Russia's Federal Antimonopoly Service https://www.worldfinance.com/strategy/apple-found-guilty-of-price-fixing)(Vertical cartel.)
Apple	(2015) Apple Inc. "Apple" and five book publishing companies conspired to raise, fix, and stabilise the retail price for newly released and bestselling trade e-books (DoJ https://www.leagle.com/decision/infco20150630133) (European Commission https://www.theguardian.com/books/2011/dec/06/ebooks-price-fixing-apple-inquiry) (Vertical cartel.)
Amazon	(2021) Allegations that a deal between the company and five book publishers has created higher prices on e-books. (US District Court https://www.hbsslaw.com/sites/default/files/case-downloads/amazon-ebooks-price-fixing/01.14.21-complaint.pdf))(Vertical cartel.)
Amazon	(2022) Guaranteed third-party sellers a minimum payment for product sales "in exchange for their agreement to stop competing with Amazon for the pricing of their products" (US class action https://www.atg.wa.gov/news/news-releases/ag-ferguson-investigation-shuts-down-amazon-price-fixing-program-nationwide) (Vertical cartel.)
Amazon	(2016) Two online sellers of posters and frames involved in illegal price-fixing cartel on Amazon's UK website. (Competition Market Authority https://www.gov.uk/government/case-studies/online-sellers-price-fixing-case-study)) (Cartel happening within platform.)
Amazon	(2022) Three sellers charged with conspiring with others to fix prices of DVDs and Blu-Ray Discs sold through the Amazon Marketplace. (DoJ https://www.justice.gov/opa/pr/three-amazon-marketplace-sellers-plead-guilty-price-fixing-dvds-and-blu-ray-discs-ongoing)) (Cartel happening within platform.)
Microsoft	(2018) Microsoft allegedly entered into unlawful contracts with competitors, personal computer makers and independent software vendors since 1988.(Supreme Court of British Columbia https://www.strosbergco.com/wp-content/uploads/2019/01/1642759-1.pdf)(Horizontal cartel)
Microsoft	(2009) An undisclosed retailer worked with Microsoft to set the price of Microsoft's Office Home and Student 2007 software packages before the companies jointly launched an ad campaign. (Bundeskartellamt https://www.hollywoodreporter.com/business/business-news/germany-fines-microsoft-price-fixing-82227/) (Cartel happening within platform.)

Table A3: Top 10 companies Standard & Poor 500 Stocks by index weight

1980		1985		1990	
Int'l Bus. Machines	4.27%	Int'l Bus. Machines	6.37%	Int'l Bus. Machines	2.95%
AT&T Corp	3.85%	Exxon Corp	2.71%	Exxon Corp	2.94%
Exxon Corp	3.76%	General Electric	2.21%	General Electric	2.30%
Standard Oil, Indiana	2.52%	AT&T Corp	1.78%	Philip Morris Cos	2.19%
Schlumberger, Ltd	2.41%	General Motors	1.48%	Royal Dutch Petrol	1.92%
Shell Oil	1.94%	Royal Dutch Petrol	1.12%	Bristol-Myers Squibb	1.61%
Mobil Corp	1.85%	DuPont	1.09%	Merck & Co	1.59%
Standard Oil of Cal	1.84%	Amoco Corp	1.07%	Wal-Mart Stores	1.56%
Atlantic Richfield	1.62%	Bell South Corp	0.99%	AT&T Corp	1.50%
General Electric	1.50%	Sears, Roebuck	0.94%	Coca-Cola Co	1.42%
	25.56%		19.76%		19.98%

1995		2000		2005	
General Electric	2.62%	General Electric	4.07%	General Electric	3.21%
AT&T Corp	2.25%	Exxon Mobil	2.59%	Exxon Mobil	3.03%
Exxon Corp	2.20%	Pfizer, Inc	2.49%	Microsoft Corp	2.41%
Coca-Cola Co	2.03%	Citigroup Inc	2.46%	Citigroup Inc	2.13%
Merck & Co	1.76%	Cisco Systems	2.36%	Procter & Gamble	1.71%
Royal Dutch Petrol	1.65%	Wal-Mart Stores	2.03%	Wal-Mart Stores	1.69%
Phillip Morris Cos	1.64%	Microsoft Corp	1.98%	Bank of America	1.61%
Procter & Gamble	1.24%	Amer Intl Group	1.97%	Johnson & Johnson	1.55%
Johnson & Johnson	1.21%	Merck & Co	1.85%	Amer Intl Group	1.54%
Microsoft Corp	1.13%	Intel Corp	1.73%	Pfizer, Inc	1.49%
	17.73%		23.53%		20.37%

2010		2015		2020	
Exxon Mobil	3.08%	Apple Inc	3.03%	Microsoft Corp	5.10%
Apple Inc	2.47%	Google Inc	2.75%	Apple Inc	4.80%
Microsoft Corp	2.00%	Microsoft Corp	2.29%	Google Inc	3.20%
Berkshire Hathaway	1.66%	Berkshire Hathaway	1.68%	Amazon.com Inc	3.10%
General Electric	1.63%	Exxon Mobil	1.68%	Facebook Inc	1.90%
Wal-Mart Stores	1.61%	Amazon.com Inc	1.63%	Berkshire Hathaway	1.60%
Google Inc	1.59%	General Electric	1.61%	JP Morgan	1.60%
Chevron Corp	1.54%	Facebook Inc	1.52%	Johnson & Johnson	1.50%
Int'l Bus. Machines	1.52%	Johnson & Johnson	1.47%	Visa	1.30%
Procter & Gamble	1.51%	Wells Fargo	1.43%	Procter & Gamble	1.10%
	18.61%		19.09%		25.20%

Note: Part of this table can be found at `https://tinyurl.com/ytb7k3p4` (consulted on 10 August 2022).