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Abstract

This article derives a European Herfindahl-Hirschman concentration index from 15 micro-aggregated country datasets. In the last decade, European concentration rose due to a reallocation of economic activity towards large and concentrated industries. Over the same period, productivity gains from reallocation accounted for 50% of European productivity growth and markups stayed constant. Using country-industry variation, we show that changes in concentration are positively associated with changes in productivity and allocative efficiency. This holds across most sectors and countries and supports the notion that rising concentration in Europe reflects a more efficient market environment rather than weak competition and rising market power.

Keywords: allocative efficiency, European market structure, firm concentration, market power, productivity

JEL classification: D24, E25, F15, L11, L25

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1 Introduction

Recent work brought attention to an US phenomenon of high and rising market concentration that has been associated with the "rise of superstar firms", which refers to a concentration of domestic economic activity in a few large and highly productive firms (Autor et al. (2017, 2020). The economic consequences of this rise in firm concentration have been intensively debated in the profession in the past few years.[1] Much of this debate centers on the key question of what rising market concentration implies for market structures and the competitive environment. On one hand, increasing concentration could signal a smoothly functioning market environment rewarding the most efficient producers with increased market share in an intense "winner takes it all" competition (Autor et al. (2020); Van Reenen (2018)). On the other hand, rising concentration could reflect a decrease in competition associated with increases in market power that are disconnected from technological advances at top firms (De Loecker et al. (2020); Covarrubias et al. (2020)).

Despite its importance, surprisingly less is known on the empirical relationship between changes in concentration, productivity, and market structure. Moreover, we still face a lack of evidence on the empirical patterns of market concentration and firm market power outside of the US and particularly for Europe. This article provides novel evidence along these dimensions.

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[1] This was the theme of the 2018 Annual Federal Reserve Symposium at Jackson Hole and several other meetings, like the CompNet Annual Conference 2019.

We use country-sector-level panel data for 15 European countries that we self-collected from mostly administrative firm-level databases.[2] Using this data, we aggregate independently derived country-specific concentration indices to derive a European Hirschman-Herfindahl concentration index (HHI) and document an increase in European concentration between 2009 and 2016 by 43%. We formally show that weighting country-level HHIs with squared revenue shares recovers precisely the European HHI as if it were computed using a merged panel of European firms. This is because the aggregate HHI can be decomposed into a series of weighted sums. We further use the decomposition properties of the HHI to study how reallocation processes affect aggregate concentration and find that European concentration is solely rising due to the reallocation of economic activity towards large and more concentrated industries, mostly located in Germany.

As a result, Germany became increasingly dominant in shaping aggregate concentration patterns. Its contribution to the European concentration level rose from 69% to 84% between 2009 and 2016 and the German manufacturing sectors alone accounts for three quarters of the European concentration level. The German dominance results from its increasingly large revenue share in Europe that enters the HHI computations in a squared way

In our robustness analysis, we exploit this key role of Germany to address the issue of our analysis being limited to a short time period, by using additional firm-level data for Germany for the years 2003 (for manufacturing, 1995) to 2017. We document a long-run increase in the German HHI, that is driven by the

[2] Confidentiality restrictions prevent combining these databases at the firm-level. The data is published as part of the CompNet database. See section 3 and online Appendix A.1.

manufacturing sector and which, given the importance of Germany for the European HHI, suggests also a long-run trend in European concentration. Using nine-digit product-level data, defining almost 6,000 distinct product categories, we also find a strong increase in market concentration at the product-level in the German manufacturing sector between 1995 and 2017.

Having established how European concentration evolved in past decades, we ask how changes in concentration relate to changes in productivity and market power, which is our second key contribution. We exploit within country-two-digit-industry-level variation in our data and relate concentration with productivity and markups. We find a strong association between concentration and aggregate productivity, whereas the connection between markups and concentration is statistically insignificant. These findings are consistent with theoretical models featuring heterogeneous firms selling differentiated goods (e.g. Melitz & Ottaviano (2008)) and differ from US-evidence in Covarrubias et al. (2020) documenting a negative (but statistically insignificant) association between concentration and productivity after 2000.

Due to its richness, our data allows us to decompose aggregate productivity into within-firm productivity and a term measuring the covariance between firm size and productivity, that we define as a measure of allocative efficiency, following Olley & Pakes (1996). We show that the entire association between concentration and productivity is driven by a positive link between concentration and allocative efficiency. This provides strong support for the view that rising European concentration is an outcome of a more efficient market environment that reallocates market shares to their most efficient use.

The connection between productivity, allocative efficiency, and concentration is highly robust to alternative concentration measures and holds for most European countries individually. It is also consistent with our results that i) a large part (50%) of European productivity growth between 2009 and 2016 results from productivity enhancing reallocation processes between firms and ii) rising European firm concentration is driven by a reallocation of market shares towards more concentrated sectors and countries over the same period.

Our study complements a large body of recent US-studies by providing European evidence on market concentration and its relation to market efficiency. Several authors documented a rise in US firm concentration over the past decades that coincides with a fall of labor's share (Autor et al. (2020)), rise in firm profits (Grullon et al. (2018)), and fall in investment rates (Gutiérrez & Philippon (2017)). Similarly, Hall (2018) and De Loecker et al. (2020) document a rise in markups over past decades in the US, while Gutiérrez & Philippon (2019, 2020) and Gutiérrez et al. (2019) argue that increased entry costs, lax antitrust enforcement, and lobbying caused a decline in US market competition. Akcigit & Ates (2019, 2021) emphasize that a decrease in knowledge diffusion between leader and follower firms accounts for these secular trends and Martin et al. (2020) highlight the role of corporate tax avoidance in contributing to the rise in US market concentration. Rossi-Hansberg et al. (2020) show that rising concentration at the US level is accompanied by a negative trend in local concentration. Crouzet & Eberly (2019) argue that investment in intangible assets of market leaders explains weak physical investment and rising concentration in the US. They further show that markups and productivity are positively correlated with investment in intangibles assets, whereas Ganapati (2020) reports a positive association between market concentration and productivity within US industries. Covarrubias et al. (2020) challenge his findings reporting negative associations between concentration and productivity after 2000.

For the European context, studies on market concentration are scarce, due to data limitations preventing researchers from combining administrative national data sources with each other – something that our approach circumvents. Among the few European studies, Cavalleri et al. (2019) document flat concentration trends in Germany, France, Spain, and Italy since 2006 using ORBIS data. Similarly, Gutierrez & Philippon (2018) argue that product market (de)regulations and antitrust enforcements induced by country-independent policy institutions created a highly competitive market environment in Europe and report flat concentration trends at the European level since 2000 using ORBIS and Compustat data. In contrast, Bajgar et al. (2019) report a steady increase in concentration in Europe since 2000 based on Multiprod data from the OECD.[3]

We contribute to this research strand in at least three ways. First, as our data is derived from mostly administrative data sources, our results are not subject to

[3] There are also several studies on changes in markups in Europe. Using Worldscope data, Diez et al. (2018) and De Loecker & Eeckhout (2020) report a strong increase in markups in Europe, between 1980 and 2016, whereas Weche & Wambach (2018) report a stable trend in markups for Europe between 2007 and 2015.

selection biases as it is the case for ORBIS and Compustat data.[4] Second, our decomposition exercise allows us to understand the relative importance of individual countries and sectors in shaping European concentration patterns. From that, we also uncover that concentration rose exclusively due to a reallocation of economic activity towards more concentrated industries. Third, in contrast to these studies, we analyze the link between concentration, productivity, market power, and allocative efficiency, and conclude that higher firm concentration is associated with a more competitive market environment in Europe. This supports a "winner-takes-it-all" mechanism driving rising concentration (Autor et al. (2017); Van Reenen (2018)) and is consistent with the conclusion in Gutierrez & Philippon (2018) that the regulatory system in Europe led to an increase in its market competitiveness over past decades.

Finally, our study relates to earlier discussions on whether rising concentration reflects higher market power or a more efficient market environment, dating back at least to Bain (1951). This includes work by Demsetz (1973, 1974), Martin (1988), or Clarke et al. (1984). For a review of this prior debate, we refer to Schmalensee (1987). The remainder of the article is structured as follows: Section 2 presents the data. Section 3 formally derives our HHI aggregation method. Section 4 shows our empirical results and section 5 concludes.

[4] Bajger et al. (2020) argue that due issues of representativeness, ORBIS data is unsuitable for cross-country comparisons and for analyzing firm distributions. Concerning market concentrations, this is particularly worrisome as changes in the firm composition (e.g. changes in the sample size) affect measured concentration indices. Online Appendix B.1 discusses the ORBIS and Multiprod data as alternative European dataset.

2 Data

2.1 The CompNet Dataset

Our main data is the CompNet dataset which contains micro-aggregated firm-level-based information at the sector-country level for 19 European countries (details on data access can be found in online Appendix A.1). We build this dataset from harmonized data collection protocols, which were executed by national statistical institutes and centrals banks in Europe on their administrative *firm-level* data. Our data collection protocols calculate various measures of firm and market performance, aggregated at the two-digit-industry (and higher) aggregation level. This includes, among others, HHI concentration indices, labor and total factor productivity measures, markups, and various firm input, output, and investment information.

Although the data is aggregated, it still contains various moments of the distributions of variables within aggregation levels (means, percentiles, standard deviations etc.). To ensure that the information of the CompNet dataset is representative and comparable, variables are weighted by firm population weights and, in case of monetary variables, deflated by PPP-adjusted deflators.[5] The dataset comes in two versions: one containing only firms with more than 20 employees (20e sample) and one featuring firms of all size classes. We focus on the 20e sample as it is available for more countries.

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[5] For details on the weighting and deflation procedures, we refer to our User-Guide (CompNet 2020b). For our concentration measures, we, however, rely on non-population weighted measures, as the population weighted HHIs are often missing in the data. We compare population weighted and non-population weighted HHIs in online Appendix C.2 and find that they are highly correlated and follow an identical trend.

Because accessing firm-level databases in Europe is usually possible only for individual countries, our CompNet data offers a unique opportunity to conduct cross-country research on issues that do not demand firm-level observations. This makes the CompNet data perfectly suited for our study on market concentration in Europe.[6]

Table 1 provides an overview on the subset of countries and sectors of the CompNet data we focus on in our analysis.[7] Our final dataset is a balanced set of countries and macro-sectors for the years 2009-2016. We refer to these years, countries, and sectors as the “balanced sample”. If appropriate, we widen the set of years for specific analyses where a balanced set of countries and sectors is not necessary (e.g. section 5.2).

Panel A shows country-level coverage information using all available years for each country. Panel B displays statistics on the sectors that we focus on during our analysis. Also, for Panel A, we only use the sectors reported in Panel B. The reported population figures are taken from Eurostat and show that the underlying firm data of CompNet accounts for a large share of active firms in most countries and sectors. In some countries, our data even covers the entire population of firms, but also in cases where the sample is smaller, the underlying firm-level datasets are the most

[6] For more details on the CompNet data, we refer to the CompNet User Guide (CompNet 2020).

[7] Although CompNet provides information on more sectors and countries, we choose this set of countries and sectors to have a comparable set of sector-country-pairs across time, which is key for our aggregation and decomposition exercises (for some countries, certain sectors are missing). We test the importance of omitted sectors in section 4.1.3 and find that our data is highly representative although we omitted the sectors “Wholesale and retail trade”, “Construction”, and “Accommodation and food service activities”.

representative datasets available for the countries included in the CompNet data due to being supplied by national banks and statistical institutes.

TABLE 1

COUNTRY AND MACRO SECTORS COVERAGE

Panel A: Country Coverage

Country	Years	Sample number firms First year	Sample number firms Last year	Population number firms First year	Population number firms Last year
	(1)	(2)	(3)	(4)	(5)
Belgium	2003-2017	4,462	7,129	8,092	8,873
Czech Republic	2005-2017	7,480	6,825	11,848	12,808
Finland	1999-2017	3,937	5,730	3,940	5,735
France	2004-2016	45,497	44,872	45,598	44,862
Germany*	2003-2016	-	-	70,103	104,288
Italy	2006-2016	38,127	40,563	48,866	46,493
Lithuania	2000-2016	2,537	3,531	2,539	3,550
Netherlands**	2007-2017	10,875	13,013	10,884	13,022
Poland	2005-2017	14,026	18,345	20,095	24,492
Portugal	2004-2017	11,006	10,531	11,033	10,561
Romania**	2005-2016	13,727	13,328	14,185	14,284
Slovakia	2000-2017	1,652	4,360	3,960	4,621
Spain	2008-2017	13,198	16,205	40,136	34,234
Sweden	2008-2016	8,533	8,894	8,861	10,061
Switzerland	2009-2017	4,296	4,089	8,922	10,337
TOTAL	2009-2016	191,711	195,142	323,550	344,623

Panel B: Macro – Sector Coverage (balanced sample)

Macro-sector	Sample number firms 2009	Last Sample number firms 2016	Population number firms 2009	Population number firms 2016
	(1)	(2)	(3)	(4)
Manufacturing	107,850	101,129	170,719	161,915
Transportation and storage	23,679	26,063	41,780	48,399
ICT	13,641	15,684	22,505	26,890
Real Estate	4,114	4,250	6,966	7,528
Professional Activities	19,877	21,904	37,067	45,196
Administrative and service	22,550	26,112	44,513	54,695
TOTAL	191,711	195,142	323,550	344,623

Note: Table 1 shows the firm coverage of our sample out of the CompNet dataset. Panel A displays country-level statistics using the first and last year of observation for each country. Panel B shows statistics for each sector, using the balanced set of countries and sectors from 2009 to 2016. CompNet data, excluding the one-digit sectors “Wholesale and retail trade”, “Construction”, and “Accommodation and food service activities”.

* Germany does not contain sample number information for confidentiality reasons.

** There is no information for the Real Estate sector for The Netherlands and Romania available.

2.2 Firm-level data on the German manufacturing sector

To complement our European analysis, we utilize rich firm-product-level panel data for Germany that was used to produce the German statistics in the CompNet data, which covers the years from 2003 (manufacturing, 1995) to 2017. This data is supplied by the German statistical offices and contains, among others, information on firm's output, costs, input decisions, products, investment decisions. For the manufacturing sector, it even contains detailed statistics on firms' product quantities and prices. The manufacturing data is limited to firms with at least 20 employees and reports some variables for the full population of firms with more than 20 employees (e.g. produced products) while other variables are collected for a representative sample of 40% of all firms. For the remaining sectors, the data consists of a 15% sample of firms with at least 17,500€ annual revenue. We provide more information on the data and on how to access it in online Appendix A.2.

We use this dataset because, as we demonstrate below, most of the extent and change in European concentration is driven by the German manufacturing sector. The German micro-data offers a long time span of firm-level data to shed light on how German concentration, and thus a large part of European concentration evolved in the period before the CompNet dataset starts. This complements the brief time span of the CompNet data and addresses concerns about our European analysis starting in the great financial crisis. Using the detailed nine-digit product data we also look at long-run changes in concentration at an extremely detailed product level, defining almost 6,000 distinct product categories.

3 Deriving a European HHI from country-level datasets

We measure concentration using the HHI of firms' gross output at different aggregation levels (industries, sectors, countries, Europe). We use the HHI because it can be decomposed into sub-sums for individual industries and countries and can thus be aggregated across independently derived datasets. The HHI considers concentration along the whole firm distribution, whereas revenue shares of the largest firms focus on market concentration in a few selected firms at the top end of the distribution. However, both concentration measures are highly correlated across and within European countries (see online Appendix C.1).

We now show how to use independently derived country-level HHI's to construct a European HHI. The key to our derivation is that the aggregate HHI can be split up into smaller sums:

$$(1) \qquad HHI = \sum_{i=1}^{T} \left(\frac{r_i}{\sum_{i=1}^{T} r_i} \right)^2 = \sum_{i=1}^{T-k} \frac{r_i^2}{(\sum_{i=1}^{T} r_i)^2} + \sum_{i=T-k+1}^{T} \frac{r_i^2}{(\sum_{i=1}^{T} r_i)^2}.$$

$i = [1, \dots, k, \dots T]$ indexes firm observations of mass T, r_i denotes gross output (sales), and we suppress time indices. When the full firm population is split up into individual dataset (as in our case), we can use this decomposition to aggregate across the individual datasets to recover the aggregate concentration index. To see this, define two countries, A and B, which together contain the full population of firms, $i = [1, \dots, k, \dots T]$. A is populated by firms $i = [1, k]$ and B is populated by firms $i = [\ k + 1, T]$. Total firm output in A and B are thus $\sum_{i=1}^{T-k} r_i = r^A$ and $\sum_{i=T-k+1}^{T} r_i = r^B$, with $r^A + r^B = \sum_{i=1}^{T} r_i$. The concentration index across the full firm population is given by equation (1) above. The individual country HHIs are given by: $HHI^A =$

$\sum_{i=1}^{T-k}\left(\frac{r_i}{r^A}\right)^2$ and $HHI^B=\sum_{i=T-k+1}^{T}\left(\frac{r_i}{r^B}\right)^2$. The HHI of $A+B$ (e.g. Europe, the world) can be expressed as a weighted average of these formulas, where the weights are the squared output shares of each country in total output across of the firm population:

$$HHI = HHI^A\left(\frac{r^A}{\sum_{i=1}^{T} r_i}\right)^2 + HHI^B\left(\frac{r^B}{\sum_{i=1}^{T} r_i}\right)^2$$

$$(2) \qquad = \sum_{i=1}^{T-k}\left(\frac{r_i}{r^A}\right)^2\left(\frac{r^A}{\sum_{i=1}^{T} r_i}\right)^2 + \sum_{i=T-k+1}^{T}\left(\frac{r_i}{r^B}\right)^2\left(\frac{r^B}{\sum_{i=1}^{T} r_i}\right)^2$$

Using $r^A + r^B = \sum_{i=1}^{T} r_i$, gives:

$$HHI = \sum_{i=1}^{T-k}\left(\frac{r_i}{r^A}\right)^2\left(\frac{r^A}{r^A+r^B}\right)^2 + \sum_{i=T-k+1}^{T}\left(\frac{r_i}{r^B}\right)^2\left(\frac{r^B}{r^A+r^B}\right)^2,$$

$$(3) \qquad = \sum_{i=1}^{T-k}\left(\frac{r_i}{r^A+r^B}\right)^2 + \sum_{i=T-k+1}^{T}\left(\frac{r_i}{r^A+r^B}\right)^2,$$

which is equivalent to equation (1). Hence, we can use independently derived country-level HHIs to derive the aggregate HHI as if the datasets would have been merged. While we focus on the European context, where administrative firm-level data is only available for individual countries and cannot be combined across countries due to data confidentiality restrictions, our simple sum-decomposition can be applied to also derive concentration indices for the world or its sub-regions, like the transatlantic market, without requiring a merge of country-specific datasets.

Note that our European concentration index focuses on sales of domestic firms and does not include any adjustment for international trade, beyond the European level. We are explicitly interested in these European firms as we want to understand how European firm performance and reallocation processes within Europe relate to market concentration.

Another important point highlighted by the above decomposition is that the appropriate weights to aggregate HHIs are *squared* output shares. Using non-squared output shares to aggregate HHIs (e.g. Cavalleri, et al. (2019), Rossi-Hansberg et al. (2020)) underestimates the role of large entities (firms, industries, countries) for the aggregate HHI. As we show, due to these squared weights, European firm concentration is mostly determined by the extent of firm concentration within a few large countries and sectors.

4 Empirical results

This section presents our empirical results. Section 4.1 discusses European-country- and industry-level evidence on firm concentration in Europe. There, we also show that: i) markups are small and stable in Europe compared to recent evidence for the US, ii) rising European concentration is a result of reallocation processes between country-sector pairs, and iii) the German manufacturing sector accounts for most of the European concentration level. Motivated by this last result, section 4.2 analyzes long-run changes in market concentration in Germany.

4.1 European firm concentration

4.1.1 Aggregate changes

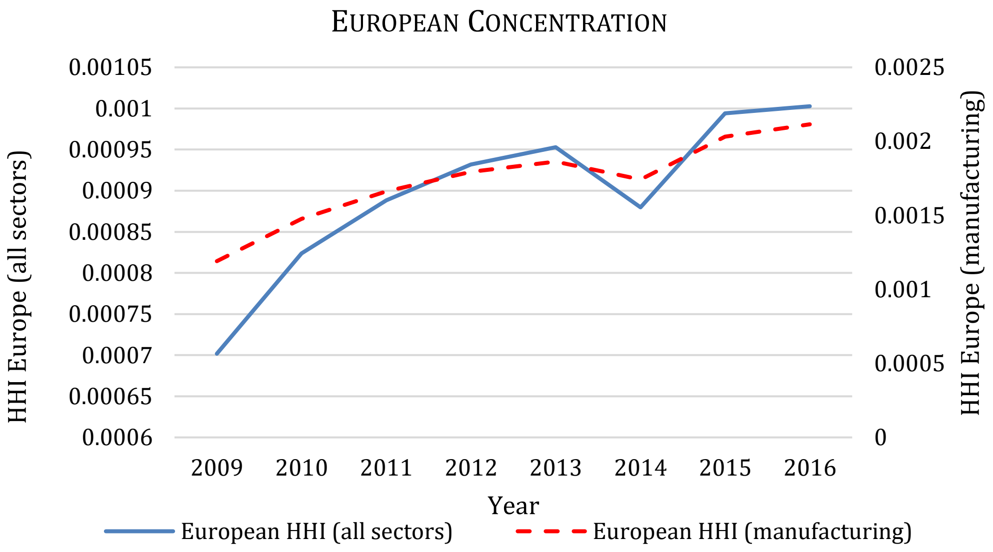

FIGURE 1 – European firm concentration. The blue solid (red slashed) line shows the European Hirschman-Herfindahl index for all sectors (the manufacturing sector) of our balanced sample for 2009 to 2016. CompNet dataset.

Figure 1 presents the evolution of firm concentration in Europe since 2009 using our HHI aggregation. We find a consistent increase in concentration over the past years in Europe. Aggregate concentration (left axis) as measured by the HHI rose by almost 50%. Concentration in the manufacturing sector (right axis) even doubled. This increase in concentration, which is particularly strong in manufacturing, is comparable to evidence for the US (Gutiérrez & Philippon (2017); Rossi-Hansberg et a. (2020)).

Table 2 displays country-specific changes in concentration and aggregate markups. Periods vary by country to display the largest possible time spans. To recover aggregate markups, we follow the production function approach of De Loecker & Warzynski (2012) and base our markup estimate on firms' input decision for intermediates (see online Appendix D for details).[8] Our CompNet dataset directly includes these markup estimates at the industry, sector, and country level as cost and sales weighted aggregates. To derive the markup expressions in Table 2, we start from sector-level aggregate markups and aggregate them further to the country level (this ensures a harmonized set of sectors across countries). We focus on cost-weighted markups as these recover the true aggregate markup under standard preferences (Edmond et al. (2018)). The average HHI and markup refer to the average aggregate values of these variables over the country-specific and European time spans. The Δ indicates changes in aggregates between the first and last year of observation.

Levels of concentration strongly vary across countries, reflecting differences in industry and market structure and country size. Although European firm concentration increased, 10 out of 15 countries display a decrease in concentration. Coinciding with the comparably large change in European concentration, the aggregate product markup increased by only one percentage point.[9] Also, changes in country-level markups are not systematically related to changes in concentration and are stable. In terms of levels, markups differ across countries, with Italy and France having values of 1.47 and 1.32, and Germany and Finland having values of 1.10 and 1.09, respectively. Overall, our markup estimates and their changes for

[8] We assume that intermediates are flexible inputs and intermediate input prices are exogenous to firms. Therefore, the markup term we apply can also be viewed as "product market power". For studies separating product and input market power using an extension of the De Loecker & Warzynski (2012) framework, see Mertens (2020a, 2020b, 2020c) and Morlacco (2019).

[9] This does not necessary contradict results on De Loecker & Eeckhout (2020). These authors rely on a very restricted set of firms, while we focus on a much larger and much more representative sample of firms. Further, De Loecker & Eeckhout (2020) use a firm market power measure that, if labor markets are non-competitive, combines labor and product market power. Hence, their measure does not necessarily only measure product markups. For discussion, see Mertens (2020b).

Europe are *much lower* than evidence reported by De Loecker et al. (2020) for the US[10]

The two take-away-messages from Table 2 are: First, judging from our markup estimates, European markets have not experienced a rise in market power in the latest years as documented for the US (where a considerable part of the rise in markups occurred between 2009 and 2016 (De Loecker et al. (2020)). Second, given that firm concentration falls in 10 out of the 15 countries, the aggregate European market concentration must be driven by a few countries and/or reallocation processes between countries.

A natural concern is whether the rise in concentration observed in Figure 1 and is part of a longer trend or whether it reflects a recovery after the great financial crisis. As long time series of firm-level data are not available for almost all countries, we address this question by first showing that Germany accounts for most of the level and changes in European firm concentration (section 4.1.3) and by subsequently studying market concentration for Germany over a much longer time span in section 4.2. There, we show that concentration follows a long-run upward trend in Germany starting well before the financial crisis. Given the German

[10] We do not want to put too much emphasize on the level comparison, because our and existing markup estimates might suffer biased level estimates introduced from incorrectly estimating the production function (e.g. due to the lack of firm-specific price data). To a certain extent this also applies to estimated changes over time. Yet, there is literally no possibility to get firm-specific price data for a set of multiple countries in Europe. To make progress in research, we therefore stick to the best possible approach, which is to derive markup estimates using a harmonized data collection protocol across 15 (and more) countries in Europe. For studies dealing with the "price-bias" when estimating markups see De Loecker, Goldberg, Khandelwal, & Pavcnik (2016) and Mertens (2020b).

importance for the European concentration level, this provides evidence that also at the European level, the rise in concentration is part of a long run trend.[11]

TABLE 2

AGGREGATE CONCENTRATION AND MARKUPS, COUNTRY-LEVEL

Country	Average HHI (times 100) (1)	ΔHHI (times 100) (2)	Average Markup (3)	ΔMarkup (4)
Belgium (2003-2017)	0.45	-0.03	1.14	0.04
Czech Republic (2005-2017)	0.80	0.37	1.14	0.08
Finland (1999-2017)	0.73	-0.35	1.09	0.05
France (2004-2016)	0.20	0.09	1.32	0.07
Germany (2003-2016)	0.62	0.05	1.10	0.04
Italy (2006-2016)	0.13	0.02	1.47	0.05
Lithuania (2000-2016)	0.54	-0.35	1.12	0.06
Netherlands (2007-2017)*	0.78	-1.10	1.11	0.01
Poland (2005-2017)	0.16	-0.11	1.17	0.03
Portugal (2004-2017)**	0.36	-0.02	1.21	-0.01
Romania (2005-2016)	0.40	-0.36	1.12	0.01
Slovakia (2000-2017)	2.50	-1.34	1.12	0.06
Spain (2008-2017)	0.56	-0.26	1.25	0.00
Sweden (2008-2016)	0.60	-0.06	1.27	-0.02
Switzerland (2009-2017)	1.21	0.26	1.23	-0.02
Europe (2009-2016)	0.09	0.03	1.18	0.01

Notes: Table 2 shows aggregate Hirschman-Herfindahl concentration indices and markups for all countries in our sample. Concentration indices are aggregate from our set of sectors as described in section 3. Markups are calculated following De Loecker & Warzynski (2012) and using gross-output production function estimates based on OLS. Markups are derived from the firms' first order conditions for intermediate inputs and aggregated using intermediate input cost weights. Averages (columns 1 and 3) reflect the average of country-level aggregates over the entire time span. Δ indicates changes between the first and last year for each country. CompNet Dataset.

* Markup data for The Netherlands ends in 2016. ** Markup data for Portugal starts in 2010.

[11] Consistent with that, if we exclude Germany from the sample, the European concentration *decreases* between 2009 and 2016 (see online Appendix H.1).

4.1.2 Within vs. Between changes

We can decompose the aggregate change of the HHI into changes within and between countries and sectors using a decomposition approach similar to Olley & Pakes (1996). In particular, it holds that:

$$HHI_t = \sum_{n=1}^{N} \left(HHI_{nt} \left(\frac{r_{nt}}{\sum_{i=1}^{T} r_{it}} \right)^2 \right) = \sum_{n=1}^{N} HHI_{nt} * s_{nt}$$

$$= \sum_{n=1}^{N} (HHI_{nt} + \overline{HHI} - \overline{HHI})(s_{nt} + \bar{s} - \bar{s})$$

$$= N * \bar{s} * \overline{HHI} + \sum_{n=1}^{N} (HHI_{nt} - \overline{HHI})(s_{nt} - \bar{s})$$

$$= N * \bar{s} * \overline{HHI} + cov(HHI_{nt}, s_{nt}). \tag{4}$$

n denotes countries (or alternatively country-sector pairs) and HHI_t is the European HHI. Variables with a bar indicate mean values.

The second term measures the covariance between countries' squared revenue shares and HHIs. Changes in this covariance reflect changes in aggregate concentration due to a reallocation of markets shares *between* countries.

The first term of equation 4 captures changes in the aggregate HHI due to changes in average HHIs within countries and is rescaled by the sum of average squared revenue shares of countries. This accounts for the HHI being decreasing in the number of firms (aggregating two countries with identical HHIs must lead to a lower aggregate HHI). We interpret this first term as the "within-country change" in European concentration.[12]

We apply two versions of this decompositions. Once, at the country and once at the sector level. We expect that if a winner-takes-it-all mechanism is driving rising concentration (i.e. if rising concentration is reflecting an efficient market outcome), increasing concentration should particularly be driven by reallocation processes reflected in an increase in the covariance term. This would reflect that market size is an important driver of concentration. Such a mechanism is also present in standard models with heterogeneous-productivity firms (e.g. Melitz (2003)), where an increase in firms' market size causes an efficiency enhancing reallocation of economic activity towards the most productive (and largest) producers leading to a higher degree of concentration.

Table 3 shows that the entire change in European firm concentration is driven by reallocation processes between countries and macro-sectors. Although more concentrated countries and sectors are on average smaller (negative covariances), there is a clear reallocation of market shares towards more concentrated countries and sectors that drives the aggregate increase in European concentration. This is reflected in increasing covariance terms in Table 3 and explains explain why concentration is rising in the aggregate, while declining in many countries.

[12] Note that one can decompose equation (4) further into $\overline{HHI} + \overline{HHI}(N\bar{s} - 1) + cov(HHI_{nt}, s_{nt})$. Where $\overline{HHI}$ equals the classical „within-term" of the Olley & Pakes (1996) decomposition. As the sum of squared market shares converges to unity, $\overline{HHI}(N\bar{s} - 1)$ converges to zero and our decomposition becomes identical to the original Olley & Pakes (1996) decomposition. The term $\overline{HHI}(N\bar{s} - 1)$ scales the within-component, $\overline{HHI}$, to the level of the aggregate HHI. In online Appendix H.2, we decompose aggregate changes in the HHI into these three components and again find that most of the aggregate change in the HHI is driven by reallocation processes. Changes in $\overline{HHI}$ display a negative contribution.

Moreover, it is consistent with the notion that changes in the market size of particularly large and efficient producers are behind changes in European concentration. In section 5, we discuss this further and uncover a strong and robust association between concentration, aggregate productivity, and productivity enhancing reallocation processes.

TABLE 3

HHI-DECOMPOSITION,
WITHIN VS. BETWEEN COUNTRY AND SECTOR CHANGES

Year	Aggregate HHI (times 100) (1)	Country-level decomposition: Within-country (times 100) (2)	Country-level decomposition: Between-country (times 100) (3)	Sector-level decomposition: Within one-digit sector (times 100) (4)	Sector-level decomposition: Between one-digit sector (times 100) (5)
2009	0.070	0.096	-0.026	0.164	-0.094
2010	0.082	0.106	-0.024	0.160	-0.078
2011	0.089	0.105	-0.017	0.150	-0.061
2012	0.093	0.107	-0.014	0.152	-0.059
2013	0.095	0.102	-0.007	0.162	-0.067
2014	0.088	0.104	-0.016	0.157	-0.069
2015	0.099	0.100	-0.001	0.144	-0.044
2016	0.100	0.098	0.002	0.154	-0.053
Percentage contribution 2009-2016	42.87%	3.53%	39.34%	-15.07%	57.94%

Notes: Table 3 shows the HHI decomposition from equation (4) at the country (columns 2 and 3) and sector (columns 4 and 5) level. Column 1 shows the level of the European HHI, while columns 2-5 show the levels of the within and between components that sum up to the aggregate HHI. The last row shows the percentage change of the aggregate HHI in column 1 over the entire time span (2009-2016). Columns 2-5 of the last row display the percentage point contribution of the within and between terms to the entire decline in the HHI. Balanced sample of countries and sectors. CompNet Dataset.

4.1.3 The role of large countries and sectors

We documented that rising European concentration is an outcome of more concentrated sectors becoming larger over time. As our HHI aggregation is based on a weighted sum, we can separate the contribution of individual countries and sectors to European firm concentration by calculating the shares of countries and sectors in the total sum of the HHI. Consider again our two-country example.

Equation (2) shows that the aggregate HHI is a weighted sum of the HHI from country A and B: $HHI = HHI^A \left(\frac{r^A}{\sum_{i=1}^{T} r_i}\right)^2 + HHI^B \left(\frac{r^B}{\sum_{i=1}^{T} r_i}\right)^2$. The contribution of country A refers to the first term on the right hand-side.

Using this sum-decomposition, Table 4 shows the contribution of individual countries to the aggregate concentration index. The picture is striking. Germany accounts for 69% of total European firm concentration in 2009. Over time, the contribution of Germany to the aggregate concentration index increases to 84.

TABLE 4

COUNTRY CONTRIBUTION TO EUROPEAN HHI, 2009-2016

Country	HHI contribution 2009 (in %) (1)	HHI contribution 2016 (in %) (2)	HHI 2009 (times 100) (3)	HHI 2016 (times 100) (4)	Revenue Share 2009 (in %)	Revenue Share 2016 (in %)
Belgium	0.71	0.57	0.37	0.45	3.66	3.57
Czech Republic	1.15	1.63	0.57	0.99	3.76	4.07
Finland	0.31	0.10	0.95	0.54	1.52	1.38
France	5.24	3.79	0.19	0.23	13.75	12.85
Germany	69.05	84.12	0.47	0.71	31.99	34.47
Italy	4.04	1.27	0.18	0.11	12.42	10.79
Lithuania	0.01	0.01	0.50	0.31	0.36	0.49
Netherlands	2.34	1.03	0.77	0.50	4.63	4.55
Poland	0.79	0.54	0.16	0.11	5.83	6.90
Portugal	0.12	0.07	0.34	0.32	1.59	1.46
Romania	0.25	0.08	0.49	0.18	1.90	2.08
Slovakia	0.37	0.54	1.29	2.09	1.41	1.61
Spain	12.70	3.94	0.76	0.49	10.87	9.01
Sweden	0.80	0.42	0.68	0.56	2.89	2.74
Switzerland	2.10	1.89	1.26	1.17	3.42	4.03
Europe	100	100	0.07	0.10	100	100

Notes: Table 4 shows the contribution of each country to the European HHI measures by the percentage share of the European HHI that is accounted for by each country. Columns 1 and 2 show the HHI contribution by country for 2009 and 2016. Columns 3-6 display country HHIs and revenue shares in total European revenue for 2009 and 2016. Balanced samples of countries and sectors 2009-2016. CompNet dataset.

The large contribution of Germany can be a result of two factors: Germany being highly concentrated and/or Germany accounting for a large sales share in Europe. Table 4 displays both components for each country. Although the German HHI was neither particularly large nor small in 2009, Germany became one of the most concentrated countries in 2016. Particularly compared to other large countries

(France or Italy), the German HHI is high given Germany's size. What is more striking is the huge revenue share of the German economy. In 2009 (2016) Germany accounts for 32% (34%) of all sales in Europe. Since these revenue shares enter the HHI in a squared way, they drive most of the large contribution of Germany to the European HHI. This can be directly calculated from Table 4: the HHI contribution equals the HHI times the squared revenue share. Even if we assume counterfactually equal HHIs across countries, just by the variation of revenue shares, Germany's contribution to the HHI would be 70% in 2016. Hence, the large German contribution is a result of the high revenue shares of Germany in Europe and the increasing aggregate European HHI is mostly a result of Germany experiencing an increase in its market share and HHI.

TABLE 5

SECTOR CONTRIBUTION TO EUROPEAN HHI 2009-2016

One-digit-sector	HHI contribution 2009 (in %) (1)	HHI contribution 2016 (in %) (2)	HHI 2009 (times 100) (3)	HHI 2016 (times 100) (4)	Revenue Share 2009 (in %)	Revenue Share 2016 (in %)
Manufacturing	74.28	87.26	0.12	0.21	66.17	64.32
Transportation, storage	6.37	5.03	0.42	0.38	10.35	11.54
Information, communication	18.15	6.55	1.04	0.70	11.07	9.66
Real estate	0.09	0.12	0.27	0.54	1.55	1.49
Professional, scientific, technical activities	0.46	0.41	0.10	0.10	5.56	6.42
Administrative, support service activities	0.66	0.63	0.16	0.15	5.31	6.59
Europe	100	100	0.07	0.10	100	100

Notes: Table 5 shows the contribution of each sector of our sample of sectors to the European HHI measures by the percentage share of the European HHI that is accounted for by each sector. Columns 1 and 2 show the HHI contribution by sector for 2009 and 2016. Columns 3-6 display sector HHIs and revenue shares in total European revenue for 2009 and 2016. Balanced samples of countries and sectors 2009-2016. CompNet dataset.

Table 5 does the same decomposition for the sector level showing that manufacturing, which is particularly large in Germany, contributes by far the most to the European HHI aggregation (we discuss how our country and sector selection impacts our calculation below).

When taking this decomposition to the country-sector level, we find that on average 75% of European firm concentration is explained by the German manufacturing sector alone, followed by the Spanish and German ICT sectors, respectively accounting for 2.8% and 2.7%. The German manufacturing sector also experienced by far the largest gain in importance for explaining the European HHI, whereas the ICT sectors display a general decline in their HHI contribution. Latter is consistent with a strong increase in the number of firms within the European ICT sector (see online Appendix H.3).

Overall, our results imply that to understand most of European firm concentration, it is key to understand firm concentration in Germany and particularly its manufacturing sector.

A natural concern with our findings is that due to excluding some sectors, where other countries have particularly large firms, we overestimate the contribution of Germany.[13] We assess the scope of this potential issue by using data from Eurostat. Recap, individual countries account for a large part of the European HHI either through being highly concentrated or though having a large revenue share in Europe, with the latter being the main source of Germany's dominance. We can thus use information on country revenue shares and counterfactual assumptions on

[13] For instance, whereas Germany traditionally has large manufacturing companies (e.g. Volkswagen), other countries might have particularly large firms in other sectors, like Wholesale Trade and Retail, which is a particularly large sector in Europe. However, Germany contains also most of the largest retailers in Europe, e.g. Schwarz Group, Aldi Einkauf GmbH & Co. oHG, Edeka Group, and Rewe Combine, which ranked #1, #2, #5, and #6 among the largest retailers in Europe in 2019, respectively (Veraart Research Group BV (2021)).

countries' HHIs to recalculate the contribution of individual countries to the European HHI.

We do this in Table 6. Columns 1-3 display the country sales shares in total European sales for all countries of our sample for 2016. Colum 1 is based on the CompNet data and focuses only on our selected set of sectors. Columns 2 and 3 use public data from Eurostat and report revenue shares once for the sectors we focus on and once for the entire economy.

Although the Eurostat data implies a slightly lower revenue share for Germany, our CompNet data reproduces the relative country sizes well. Column 3 shows that including the sectors we omitted from our analysis would not fundamentally change the country revenue shares. Columns 4 reports the HHI of each country from the CompNet data based on our chosen set of sectors for 2016. Columns 5-8 compare our baseline HHI contribution with counterfactual estimates.

The findings are reassuring. Although using Eurostat weights based on the selected set of sectors of our analysis, reduces the importance of Germany, Germany still accounts for more than 75% of the European HHI level (column 6). Even if we consider sales weights based on all sectors, Germany's contribution is still 68% (column 7). In column 8 we go one step further and increase the HHI of each country except Germany by 50%. This shall account for potential mismeasurements in the HHI, for instance, due to omitting sectors where other countries are particularly concentrated (recap, however, that Germany also possesses some of the largest firms in the excluded sectors; see footnote 13). We view increasing the HHIs by 50% as an extreme (and unrealistic) test, yet it illustrates that even under an unrealistically huge mismeasurement of the HHIs, Germany is still accounting for most of the aggregate European concentration. This underlines again the key role of the (squared) revenue shares in determining the importance of individual entities for the European concentration index.

TABLE 6

COUNTERFACTUAL ESTIMATES OF COUNTRY CONTRIBUTION TO EUROPEAN HHI, 2016

	SALES SHARES COMPNET VS. EUROSTAT			HHI		COUNTERFACTUAL HHI CONTRIBUTIONS (IN %)		
Country	Sales share CompNet, sample sectors (1)	Sales share Eurostat , sample sectors (2)	Sales share Eurostat, entire economy (3)	HHI CompNet, sample sectors (times 100) (4)	HHI contribution, baseline (5)	Eurostat sales shares, sample sectors (6)	Eurostat sales shares, entire economy (7)	Column 8 + increasing the HHI of all countries but Germany by 50% (8)
Belgium	3.57	4.23	4.76	0.45	0.57	0.91	1.33	1.72
Czech Republic	4.07	2.19	1.94	0.99	1.63	0.54	0.49	0.63
Finland	1.38	1.87	1.70	0.54	0.10	0.21	0.20	0.26
France	12.85	16.44	17.03	0.23	3.79	7.00	8.69	11.24
Germany	34.47	31.40	27.11	0.71	84.12	78.88	67.99	58.61
Italy	10.79	13.06	12.55	0.11	1.27	2.11	2.26	2.92
Lithuania	0.49	0.32	0.35	0.31	0.01	0.00	0.00	0.01
Netherlands	4.55	6.13	6.65	0.50	1.03	2.12	2.88	3.73
Poland	6.90	4.08	4.12	0.11	0.54	0.21	0.24	0.31
Portugal	1.46	1.32	1.43	0.32	0.07	0.06	0.09	0.11
Romania	2.08	1.12	1.20	0.18	0.08	0.03	0.03	0.04
Slovakia	1.61	1.00	0.83	2.09	0.54	0.24	0.19	0.24
Spain	9.01	7.86	8.36	0.49	3.94	3.41	4.46	5.77
Sweden	2.74	3.99	3.82	0.56	0.42	1.00	1.06	1.38
Switzerland	4.03	4.99	8.13	1.17	1.89	3.28	10.08	13.03

Notes: Table 6 presents counterfactual estimates of the country contribution to the European HHI. Column 1-3 show different ways of calculating country sales shares in total European sales. Column 1,2, and 3 respectively use i) the CompNet data and our selected set of sectors, ii) Eurostat data based on our selected set of sectors, and iii) Eurostat data based on all sectors to construct sales weights. Column 4 shows the country-level HHIs based on the CompNet data and our selected set of countries. Column 5-8 show our baseline measures of the country contribution and subsequently alternative ways of measuring the country contribution based on i) Eurostat sales shares for the sample sectors and our baseline HHIs (column 6), ii) Eurostat sales shares for all sectors and our baseline HHIs (column 7), and iii) Eurostat sales shares for all sectors and a counterfactual HHI distribution where we double the HHI for each country except Germany (column 8). Eurostat (structural business statistics) and CompNet.

4.2 Long-run concentration trends in Germany

Whereas the CompNet data offers a rich set of information for studying concentration and productivity in Europe, it lacks individual firm-level information and features only a short time period. We therefore complement our analysis with firm-level data for Germany covering a time span from 2003 (for manufacturing, 1995) to 2017. Recap that our analysis showed that Germany (and particularly its manufacturing sector) accounts for most of the aggregate concentration patterns in Europe. Hence, to understand European firm concentration, it is key to understand firm concentration in Germany and its manufacturing sector.

Figure 3 shows how concentration evolved in Germany. Concentration indices based on the manufacturing sector dating back to 1995 are indicated by the yellow dashed (top 10 share) and blue solid (HHI) line, while the red dashed (top 10 share) and black solid (HHI) line report evidence for the full German data (the same data used to build the CompNet data). Similarly, to the European level shown in Figure 1, we find a particularly strong increase in concentration in Germany after 2008. If we go back to 1995 using the manufacturing sector data (recap, the German manufacturing sector alone accounts for 75% of the European HHI between 2009 and 2016), we find that, with somewhat of a slowdown in the early 2000s, concentration steadily rose since 1995 until the crisis. Over the past decades, the HHI in the German manufacturing sector quadrupled.[14] Concentration at the

[14] The German manufacturing sector accounts for a stable share of 22%-23% of German GDP over this period (Statistisches Bundesamt (2021)).

German-wide level, exhibits changes over time that are extremely similar to changes in the manufacturing sector, although showing am overall weaker increase.

We use the firm-level data also as a benchmark for the CompNet data in Figure 3 where we also plot HHI values for the manufacturing sector (blue dotted line with squares) and our balanced set of sectors (black dotted line with squares) next to the concentration measures directly derived from the German firm-level data. As shown, the firm-level data concentration measures are closely in line with the concentration measures reported in CompNet, particularly with respect to changes over time. This is not surprising as the firm-level data we use is exactly the one used to generate the aggregated data for Germany in CompNet. Figure 3 thus shows that any harmonizing routines of the data across European countries did not affect the representativeness and quality of the data.

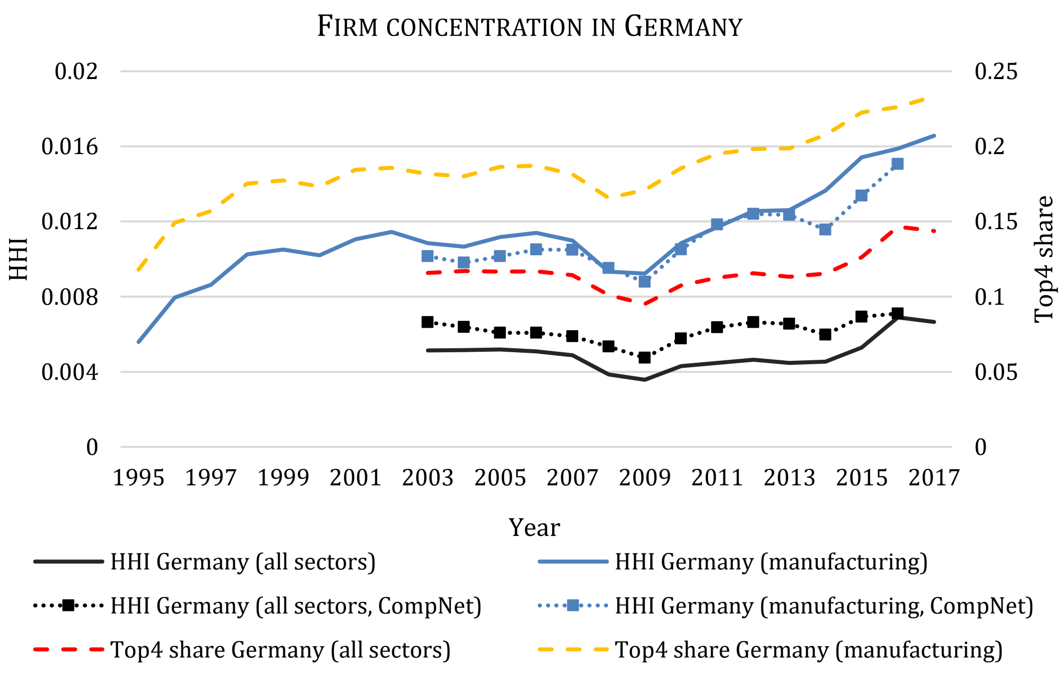

FIGURE 3 – Firm concentration in Germany. Panel A and B respectively show firm productivity-size premia estimated as specified in equation (6) for each country and each sector. All available years and countries, balanced sample of sectors. CompNet dataset.

Using detailed nine-digit product-level information, Figure 4 investigates how firm concentration changed within nine-digit manufacturing product industries in Germany. We infer on product market concentration by regressing product market HHIs on a full set of time and product dummies, from which Figure 4 plots the estimated coefficients. As products were reclassified in the years 2001/2002 (depending on the state) and 2008 together with the revision of the NACE codes, we derive the changes in product market concentration from separate regression for the periods 1995-2000, 2002-2007, and 2008-2017 and extrapolate the missing years using the previous period information. Due to this extrapolation and rescaling of coefficients, Figure 5 does not report standard errors, but the estimated regression coefficients are, except for 1996, all statistically significant to the one percent level.

Figure 4 – Product market concentration in Germany's manufacturing sector. The blue solid line displays the average product market HHI at the nine-digit product level derived from estimating separate regressions of the product market HHI on a full set of year and product dummies for the periods 1995-2000, 2002-2007, and 2008-2017. The red dashed line indicates interpolations. German firm-product-level manufacturing sector data.

As Figure 4 shows, there is an almost linear increase in product market concentration by 35% over the past decades in German manufacturing sector product markets. We thus find that concentration in the German manufacturing sector is strongly increasing at the aggregate level and within extremely detailed nine-digit product categories. Given the German importance for European concentration figures, our evidence for Germany suggests a long run increase in concentration in Europe over the past decades.[15]

5 Concentration, productivity, and allocative efficiency

This section relates changes in concentration to changes in productivity and allocative efficiency. Section 5.1 describes how European-level productivity changes in past years documenting a key role for productivity enhancing reallocation processes in explaining productivity growth. Section 5.2 uses within country-industry variation to study how concentration relates to productivity, allocative efficiency, and markups and documents a highly robust positive association between concentration, aggregate productivity, and allocative efficiency.

5.1 Productivity and allocative efficiency in Europe

As we are interested in whether higher concentration reflects a more efficient market environment or excessive market power, Table 7 first provides insights on recent European productivity dynamics. We define our productivity measures as

[15] In a related study, Mertens (2020b) reports product markups for the German manufacturing sector using a production function approach controlling for firm-level output and input price variation and addressing the well-known simultaneity bias of the production function. He shows that markups in the German manufacturing sector are low and increased by only 4 percentage points between 1995-2014, although manufacturing sector firm concentration strongly increased during that time. Online Appendix K reports these markup results and shows that the markup changes in our CompNet data, based on much less sophisticated production functions, are highly consistent with them. This further reassures us in the quality of our CompNet data.

value-added labor productivity. The advantage of this measure is that it can be aggregated across sectors and countries and can be directly calculated from the data.[16] Using the aggregation features of labor productivity, we derive a decomposition of aggregate changes in European productivity into within- and between-firm components following Olley & Pakes (1996). We decompose aggregate productivity (Ω_t) into the sum of the unweighted mean firm-level productivity ($\overline{\omega}_{it}$) and the covariance between firms' share of economic activity (s_{it}, here employment shares) and productivity ($cov_t(\omega_{it}, s_{it})$):

$$\Omega_t = \overline{\omega}_{it} + cov_t(\omega_{it}, s_{it}). \tag{5}$$

i indicates the firm-level. Changes in $\overline{\omega}_{it}$ reflect changes in aggregate productivity due to changes in within-firm productivity, whereas changes in $cov_t(\omega_{it}, s_{it})$ measure changes in aggregate productivity resulting from a reallocation of market shares between firms. Because the CompNet data does not include the underlying firm-level data but contains such productivity decompositions for the two-digit industry and sector level, we can reweight country-sector-level components of this decomposition to recover a European-level Olley-Pakes decomposition.[17]

Table 7 reports that, between 2009 and 2016, European labor productivity grew by 7.5%. Column 1 shows the percentage growth of productivity for each year and

[16] Although the CompNet data provides production function estimations and associated TFP measures, the estimated production functions are not perfectly identified as to run harmonized data collection protocols across countries, the production function estimation can only be sparsely specified. Most notably, this means that for control function approaches the demand equation for the proxy variable does only contain capital and productivity and that the production function does not include a correction for firm-specific price variation.

[17] For that, we reweight sector-level aggregate productivity with the sector-level share of employment in European employment and the unweighted mean sector-level productivity with the sector-level number of firms in the European-level number of firms. Again, we focus on our balanced sample of sectors and years.

columns 2 and 3 display the percentage point contribution of the within- and between-firm component (the sum of columns 2 and 3 yield the value of column 1). Productivity growth within firms and an increasing allocative efficiency of the European market each account for one half of European productivity growth in past years. There is thus a significant contribution of reallocation processes not only to rising concentration, but also to aggregate productivity growth.

TABLE 7

PRODUCTIVITY DYNAMICS,
2009-2016 BALANCED SAMPLE OF FIRMS AND SECTORS

Year	Aggregate productivity growth (in %) (1)	Contribution within-firm changes (in percentage points) (2)	Contribution reallocation processes (in percentage points) (3)
2009	-	-	-
2010	5.71	3.46	2.25
2011	0.73	1.60	-0.87
2012	-0.17	-0.81	0.64
2013	-0.12	-0.01	-0.10
2014	0.32	0.59	-0.27
2015	0.11	-0.51	0.62
2016	0.84	-0.38	1.22
2009-2016	7.5	3.94	3.59

Notes: Table 7 displays a European-level productivity decomposition for value-added labor productivity. Column 1,2, and 3 respectively show yearly changes in aggregate productivity, the within-firm contribution to aggregate productivity growth, and the between-firm contribution to aggregate productivity growth. Balanced sample of countries and sectors. CompNet dataset.

To analyze the relationship between concentration and productivity, we start by calculating productivity-size premiums. As the CompNet dataset does not contain individual firm-level information but reports so called "joint distributions" that report mean productivity for each decile of the size distribution within each two-digit industry-country pair, we run the following regression:

(6) $$\overline{\omega}_{jcnt} = \beta_{Size\_centile} Size\_decile_{jcnt} + \beta_{\overline{K\_L}} \overline{K\_L}_{jcnt} + \upsilon_{jn} + \upsilon_t,$$

where $\overline{\omega}$ is the log of average value-added based labor productivity of centile c within two-digit industry j at time t in country n. $\overline{K\_L}$ denotes corresponding average capital over labor ratios and $Size\_decile$ is a variable defined from 1 to 10 capturing the ten deciles of the firm size distribution (number of employees) within a two-digit industry. υ_{nj} and υ_t capture country-two-digit industry and year fixed effects. $\beta_{Size\_centile}$ is the coefficient of interest, which measures the productivity premium of moving the size distribution of an industry up by one decile.

We run this regression separately for countries and sectors and once pooled across all countries and sectors. In contrast to before, we use all available years and countries of the CompNet dataset and just exclude sectors we excluded throughout our analysis. The larger set of data points allows us to derive the parameters for a longer time span, which increases precision (replications with the balanced sample give similar results, see online Appendix E).

Figure 2 reports the resulting productivity premiums. Panel A (B) shows the productivity-size premiums for each country (sector). Across all countries, moving up one decile of the size distribution is associated with a higher firm productivity of 1.5%. Although there is considerable variation across countries, the point estimates of the productivity-size premiums are positive for each of them.

For sectors, we find large and positive size premiums in manufacturing (1.8%) and ICT (2.6%), with “Professional, scientific, technical, activities” showing a smaller but still considerably positive productivity premium. In contrast, “Administrative, support service activities” and “Transportation and storage” display negative point estimates, although statistically indistinguishable from zero for "Administrative, support service activities".[18]

FIRM PRODUCTIVITY-SIZE PREMIA IN EUROPE

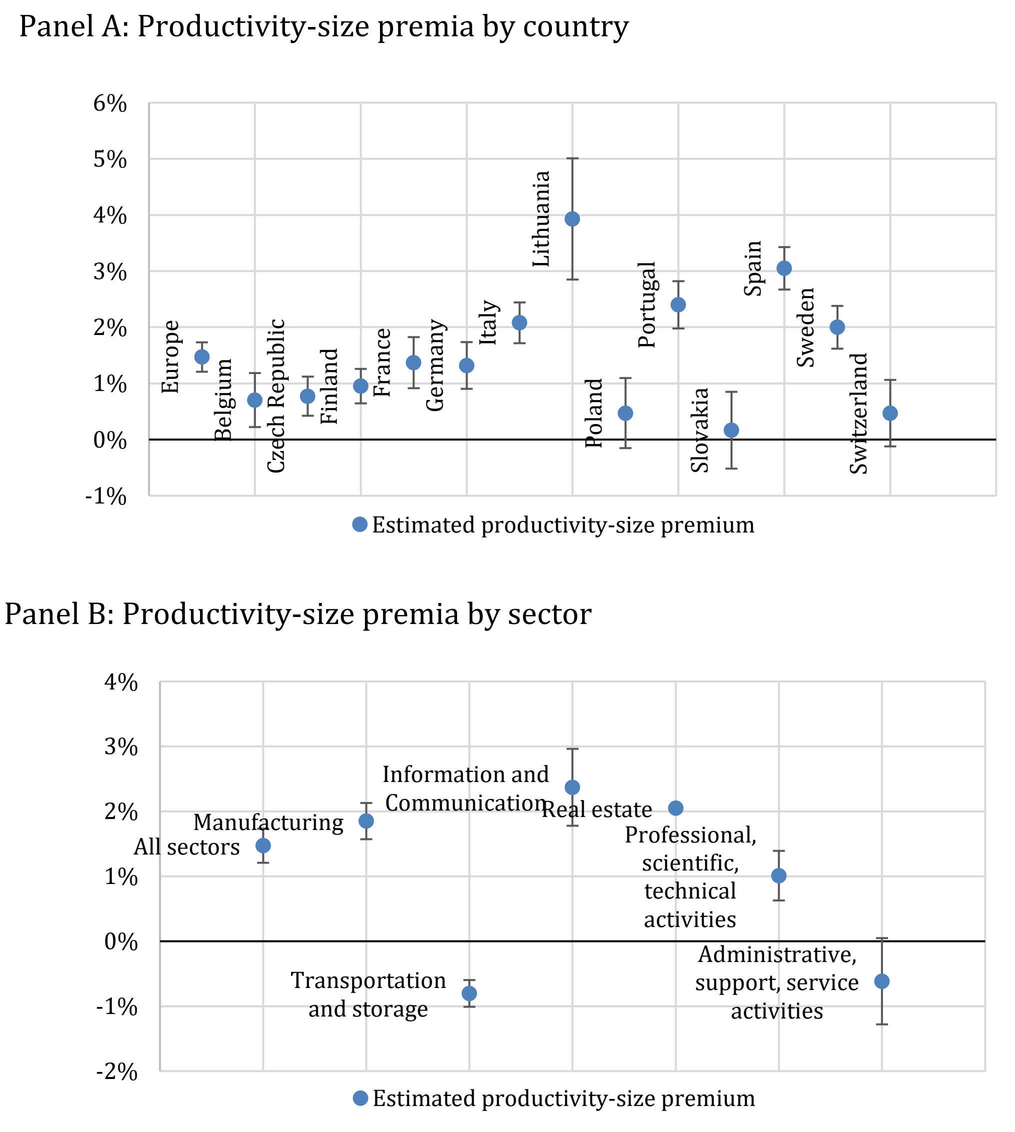

FIGURE 2 – Firm productivity-size premia in Europe. Panel A and B respectively show firm productivity-size premia estimated as specified in equation (6) for each country and each sector. All available years and countries, balanced sample of sectors. Standard errors are clustered at the sector-level. The Netherlands and Romania are excluded due to missing values in the joint distributions we use. CompNet dataset.

[18] We tested whether the productivity-size premiums change over time and found them to be constant. This is consistent with results in section 5.2 showing that the positive association between concentration and aggregate productivity is not a result of a higher average firm productivity, but an outcome of a more efficient resource allocation.

5.2 Regression analysis

To understand how changes in concentration relate to changes in productivity and markups, we perform the following fixed-effects regression analysis on the two-digit industry level:

$$HHI_{njt} = \beta_{\Omega}\Omega_{njt} + \boldsymbol{C}_{njt1}^{'}\boldsymbol{\gamma} + \upsilon_{nj} + \upsilon_{t}. \tag{7}$$

HHI_{njt} and Ω_{njt} denote two-digit industry-level HHIs (we multiply HHI values by 100) and productivity in thousands of value-added units per employee (industry-level productivity is an employment weighted average of firm-level productivity, ω_{nijt}). $\boldsymbol{C}'_{njt1}$ is a vector of control variables, including, depending on the specification, average firm size, industry-level markups (calculated as in online Appendix D), and industry-level capital over labor ratios. Controlling for capital over labor ratios accounts for potential changes in (labor) productivity that result from changing capital intensities but do not reflect true productivity gains. Therefore, we control for this variable in all our productivity regressions. The inclusion of industry-country and year fixed effects (υ_{nj} and υ_{t}) ensures that we identify our coefficients from changes within industries.[19]

We explicitly model HHIs as a function of productivity (and markups) as we want to understand whether concentration is an outcome of a more efficient market environment or higher firm market power (we discuss reverse causality below).

[19] An apparent alternative to equation (7) would be a regression model in first differences. We prefer the fixed effects model as it uses the same source of identifying variation (within-industry) but avoids a disproportional loss due to missing values. Latter happens in the CompNet data due to some smaller sectors frequently not passing country-specific disclosure criteria regarding the minimum number of observations within an industry-year cell.

We run several versions of equation (7) where we also replace Ω_{njt} with alternative variables of interest (e.g. industry-level allocative efficiency). We use all available countries and industries for our regression analysis. This is because we are interested in identifying the underlying relationship between concentration and productivity in Europe rather than explaining specific data patterns. Therefore, we aim for an estimation sample that is as complete as possible.

TABLE 8

CONCENTRATION AND PRODUCTIVITY, 2-DIGIT SECTOR ANALYSIS

	HHI_{jt} (1)	HHI_{jt} (2)	HHI_{jt} (3)	HHI_{jt} (4)	HHI_{jt} (5)	HHI_{jt} (6)	HHI_{jt} (7)	HHI_{jt} (8)	HHI_{jt} (9)
$Aggregate\ producitivity_{jt}$	0.0255***	0.0241***	0.0259***						
	(0.00563)	(0.00577)	(0.00626)						
$Within-$ $firm\ productivity_{jt}$				-0.00755	-0.0110	-0.00831			
				(0.00706)	(0.00772)	(0.00735)			
$Between-$ $firm\ productivity_{jt}$							0.0699***	0.0694***	0.0698***
							(0.0214)	(0.0217)	(0.0209)
$Capital\ Intensity_{jt}$	-0.00311	-0.00310	-0.00275	-0.00103	-0.00109	-0.000787	-0.00283	-0.00284	-0.00241
	(0.00244)	(0.00243)	(0.00209)	(0.00135)	(0.00137)	(0.00110)	(0.00252)	(0.00253)	(0.00215)
$log(Avr.Firm\ Size_{jt})$			4.493**			4.183**			4.322***
			(1.718)			(1.697)			(1.567)
$log(Aggregate\ Markup_{jt})$		1.457	0.768		4.002*	3.394		0.409	-0.123
		(1.521)	(1.496)		(2.154)	(2.097)		(1.315)	(1.327)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,364	6,364	6,364	6,364	6,364	6,364	6,364	6,364	6,364
# of sectors	47	47	47	47	47	47	47	47	47
R-squared	0.791	0.791	0.799	0.785	0.786	0.793	0.805	0.805	0.812

Notes: Table 8 display regression results from estimating equation (7) using aggregate productivity (column 1-3), within-firm productivity (column 4-6), and allocative efficiency (columns 7-9) as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset.

Table 8 shows a strong and highly robust association between productivity and concentration. This is robust to the inclusion of industry-level markups (column 2) and average firm size (column 3).[20] Notably, there is no statistically significant association between markups when conditioning on productivity, implying no particular role for market power in creating an inefficient extent of concentration. Beyond that, conditioning for markups also absorbs any changes in value-based productivity due to firms charging higher markups. The coefficient on productivity remaining unchanged after controlling for markups thus proves that concentration is associated with a higher level of production efficiency.

Columns 4-6 and 7-9 apply a standard Olley & Pakes (1996) decomposition that decomposes aggregate productivity, Ω_{njt}, into a within-firm term, measuring the unweighted average across firms ($\bar{\omega}_{njt}$), and a between-firm term, measuring the covariance between firm size (employment share) and productivity ($cov_{njt}(\omega_{nijt}, s^{L}_{nijt})$). The between-firm component reflects the extent to which more productive firms are larger and we interpret it as an allocative efficiency measure. A growth of this variable over time implies that more productive firms become larger over time (get a larger share of industry employment).

Strikingly, the entire positive relation between concentration and productivity is driven a positive connection between allocative efficiency and concentration.[21] This

[20] Given the definition of the HHI as the sum of squared market shares, it is difficult to interpret the size of the coefficients in Table 10. We address this in Table 13 using the share of the ten largest firms (top 10 share) in an industry as alternative concentration measure. We find sizeable quantitative associations between concentration, productivity, and allocative efficiency. Top 10 shares are highly correlated in terms of levels and changes with HHIs (see online Appendix C.1).

[21] When regressing the productivity decompositions terms on concentration (reversing equation (7)), we can exactly measure the part of the positive association between industry-level productivity

strongly supports a winner-takes-it-all view where increasing concentration in Europe is an outcome of a more efficient market environment that features higher productivity and allocates market shares and resources to the best performing firms (Autor et al. (2017); Van Reenen (2018)).

TABLE 9

CONCENTRATION AND PRODUCTIVITY,
2-DIGIT SECTOR ANALYSIS, SEPARATELY BY COUNTRY

	$Aggregate\ productivity_{jt}$ (1)	$Within-firm\ productivity_{jt}$ (2)	$Between-firm\ productivity_{jt}$ (3)
Belgium	0.00084 (0.0077)	0.0011 (0.00743)	0.0511* (0.0265)
Czech Republic	0.0385 (0.0379)	-0.0206 (0.0349)	0.170** (0.0703)
Finland	0.0984** (0.0378)	0.145*** (0.0397)	0.150*** (0.0534)
France	0.0494*** (0.0102)	0.0227 (0.0149)	0.0698*** (0.00920)
Germany	0.0211** (0.0096)	-0.00344 (0.0217)	0.0494*** (0.0183)
Italy	0.00944 (0.00997)	0.00411 (0.0119)	0.0130 (0.0178)
Lithuania	-0.0037 (0.0794)	-0.155*** (0.0524)	0.273** (0.110)
Netherlands	0.206** (0.0916)	-0.158* (0.0912)	0.254** (0.104)
Poland	0.0393 (0.0404)	-0.0139 (0.0333)	0.0972 (0.0585)
Portugal	0.0926** (0.0375)	-0.0643 (0.0407)	0.150*** (0.0371)
Romania	-0.0424 (0.0314)	-0.0944** (0.0350)	0.0797* (0.0413)
Slovakia	-0.0359*** (0.00554)	-0.0438*** (0.00635)	-0.0128 (0.0855)
Spain	0.0082 (0.00944)	-0.0157 (0.0179)	0.0376* (0.0215)
Sweden	0.0094 (0.0139)	-0.0264*** (0.0050)	0.0470 (0.0258)
Switzerland	0.113** (0.0481)	0.0890** (0.0335)	0.128 (0.0786)

Notes: Table 9 shows regression coefficients on from estimating equation (7) separately by countries when using industry-level capital over labor ratio, average firm size, and industry-level markups as controls. Column 1, 2, and 3 respectively show coefficients when using industry-level allocative aggregate productivity, within-firm productivity, and allocative efficiency as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset.

Tables 9 and 10 estimate equation (7) including all controls (e.g. as in Table 8, column 3) separately by countries and macro sectors. Although the coefficients are not always statistically significant (partly due to having a low observation count), the association between concentration and productivity is positive for almost all countries and sectors. The negative associations between concentration and productivity we document for a few countries is mostly driven by a negative within-

and concentration due to allocative efficiency and within-firm changes. We do this in online Appendix G and find that 99% (1%) of this connection is explained by the allocative efficiency (within-firm) component.

firm coefficient (Table 9, columns 2 and 3). Strikingly, in almost every country and sector there is a strong and often highly statistically significant association between allocative efficiency and concentration.

TABLE 10

CONCENTRATION AND PRODUCTIVITY,
2-DIGIT SECTORS ANALYSIS, SEPARATELY BY MACRO SECTOR

	$Aggregate\ productivity_{jt}$ (1)	$Within-firm\ productivity_{jt}$ (2)	$Between-firm\ productivity_{jt}$ (2)
Manufacturing	0.0253* (0.0126)	-0.0 (0.0114)	0.206*** (0.0597)
Transportation, storage	0.0122* (0.00449)	-0.072* (0.0074)	0.0381*** (0.0025)
Information, communication	0.0209 (0.0111)	-0.0169 (0.0163)	0.0575** (0.0165)
Real estate*	0.0249 (-)	0.006 (-)	0.0347 (-)
Professional, scientific, technical activities	0.0579 (0.0309)	-0.0060 (0.0259)	0.117 (0.0602)
Administrative, support service activities	0.0251 (0.0150)	-0.00401 (0.0265)	0.0355* (0.0107)
High-tech, knowledge intensive	0.0314*** (0.0112)	-0.0116 (0.00740)	0.0756** (0.0270)
Low-tech, not knowledge intensive	0.0167** (0.0076)	0.00563 (0.00643)	0.0447** (0.0156)

Notes: Table 10 shows regression coefficients on from estimating equation (7) separately by sectors and by technology classes when using the industry-level capital over labor ratio, average firm size and industry-level markup as controls. Column 1, 2, and 3 respectively show coefficients when using industry-level aggregate productivity, within-firm productivity, and allocative efficiency as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet data.

* Standard errors could not be estimated for the Real Estate sector as this only consist of one industry (one cluster in our estimation.

The last two rows of Table 10 group sectors into high-tech-knowledge-intensive and low-tech-non-knowledge-intensive sectors using a classification provided by Eurostat (see online Appendix H). This speaks to the notion that the positive association between concentration allocative efficiency/productivity could be driven by high-tech and knowledge intensive industries where the development of modern technologies is associated with high sunk research costs that create dominant market positions for certain firms.

Table 10 shows, however, that concentration, productivity, and allocative efficiency are strongly associated with each other in both, high-tech-knowledge-intensive and low-tech-non-knowledge-intensive industries. This underlines a general connection between allocative efficiency, productivity, and concentration in Europe that is independent of the technological sophistication of the industry.

TABLE 11

CONCENTRATION AND PRODUCTIVITY 2-DIGIT SECTOR ANALYSIS

	$Top10_{jt}$	$Top10_{jt}$	$Top10_{jt}$	$Top10_{jt}$	$Top10_{jt}$	$Top10_{jt}$
	(1)	(2)	(3)	(4)	(5)	(6)
$Aggregate\ producitivity_{jt}$	0.0496***	0.0511***				
	(0.0120)	(0.0132)				
$Within-firm\ productivity_{jt}$			0.0247*	0.0259*		
			(0.0131)	(0.0144)		
$Between-firm\ productivity_{jt}$					0.0950***	0.0921***
					(0.0280)	(0.0271)
$Capital\ Intensity_{jt}$	0.000518	0.00115	0.00267	0.00319	0.00179	0.00251
	(0.00221)	(0.00270)	(0.00323)	(0.00375)	(0.00230)	(0.00287)
$log(Avr.Firm\ Size_{jt})$		7.973***		7.789***		7.557***
		(1.590)		(1.621)		(1.546)
$log(Aggregate\ Markup_{jt})$		0.336		3.127		1.146
		(2.541)		(2.663)		(2.407)
Time FE	YES	YES	YES	YES	YES	YES
Country-industry FE	YES	YES	YES	YES	YES	YES
Observations	5,820	5,820	5,820	5,820	5,820	5,820
# of sectors	47	47	47	47	47	47
R-squared	0.943	0.946	0.941	0.944	0.944	0.946

Notes: Table 11 displays regression results from estimating equation (7) using the Top10 share as dependent variable and aggregate productivity (column 1-2), within-firm productivity (column 3-4), and allocative efficiency (columns 5-6) as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset.

Finally, Table 11 uses the share of the largest 10 firms within an industry as an alternative concentration measure and finds that our results are extremely robust also to this specification.[22] A one-unit increase in industry-level productivity is

[22] The sample in Table 11 is smaller compared to our baseline estimates. This is because some countries did not agree to publish the top 10 share in the CompNet data for confidentiality reasons.

associated with a five-percentage point higher revenue share of the ten largest firms – a huge effect.[23] Again, there is a particularly strong association between concentration and allocative efficiency.

Online Appendix F provides several additional robustness tests and replicates our main regression results i) for a total factor productivity measure derived from a production function estimation, using ii) cross-sectional variation between industries for identification, and iii) lagged values of our productivity variable. Latter accounts for reverse causality issues. Our results hold across all these additional specifications.

Overall, our result show that concentration is strongly positively associated with higher productivity and a more efficient allocation of resources in Europe. This provides strong support for the "positive view" of rising concentration in Europe and is consistent with our findings that i) the increase in concentration in Europe was mostly an outcome of reallocation processes towards more concentrated sectors and countries and ii) reallocation processes being a key driver of aggregate productivity growth in Europe.

6 Conclusion

This article studies firm concentration and its relation to productivity, market power, and allocative efficiency in Europe. In a large data collection effort, we derive a European HHI from 15 independently constructed country-sector-level datasets

[23] Recap, labor productivity is defined in terms of thousands of real value-added units per employee (in 2005 values).

based on detailed firm-level data. The data we collected is published as part of the 7th CompNet vintage and can be readily accessed by researchers.

We document an increase in European firm concentration by 43% that is driven by a reallocation of economic activity towards concentrated sectors and countries. Germany, and most notably its manufacturing sector, is accounting for most of the increase in European concentration.

Coinciding with the rise in concentration, we document that i), in contrast to recent US evidence (e.g. De Loecker et al. (2020)), markups are low and stable in Europe and ii) that productivity enhancing reallocation processes are a strong driver of European productivity growth in past years.

We test the association between changes in firm concentration, productivity, allocative efficiency, and markups using country-industry variation. Changes in concentration and strongly positively associated with changes in allocative efficiency and aggregate productivity, whereas changes in markups are statistically unrelated to changes in firm concentration. Our findings are consistent with the aggregate patterns of concentration, allocative efficiency, and markups in Europe and support the view that higher concentration reflects an efficient market outcome in Europe where more productive firms are rewarded with higher market shares.

Our study has important consequences for industrial and antitrust policy in Europe. As concentration is associated with higher market efficiency and statistically unrelated to markups, rising concentration must not be, prima facie, a cause of concern. The assessment regarding the detrimental consequences of excessive market power must thus be based on direct measures of that market power and its associated rents rather than relying on the observed increases in concentration.

Building on our findings, we see two critical issues for future research. First, we did not consider multinational firms in our analysis as data restrictions prevent a combination of individual country-level firm databases. Although our concentration measure is the best possible estimate for Europe given these restrictions, it is an important next step to assess the importance of multinational corporate groups in shaping the global market environment. Second, while we study the relationship of concentration with productivity and product market power, we did not comment on labor market impacts of firm concentration.[24] We hope that this article will contribute to encouraging fruitful discussions on these and related topics.

[24] For evidence on the relationship between concentration and inequality in Europe, see Cortes & Tschopp (2020).

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Online Appendix – not for publication

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Appendix A: Data

Appendix A.1: The CompNet Dataset

The CompNet dataset is collected by the Competitiveness Research Network. The network is hosted by the Halle Institute for Economic Research (IWH) and includes several partner institutions: European Commission, European Central Bank (ECB), European Bank for Reconstruction and Development, European Investment Bank, France Stratégie, German Council of Economic Experts and Tinbergen Institute. Since 2017 the Scientific Team is composed by IWH and ECB members.

The CompNet dataset includes micro-aggregated indicators derived from balance sheet data from 19 European Countries and for the period 1999-2017. Data are aggregated at country, 1-digit Macro Sector, 2-digit Sector and NUTS 2-digits level.

The dataset, in its 7th Vintage release, includes 19 countries: Belgium, Croatia, Czech Republic, Denmark, Finland, France, Germany, Hungary, Italy, Lithuania, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden and Switzerland.

Macro Sectors are available according to NACE 2 classification and are:

- Manufacturing (1),
- Construction (2),
- Wholesale, retail trade, repair of motor vehicles and motorcycles (3),
- Transportation and Storage (4),
- Accommodation and food service activities (5),
- Information and communication (6),
- Real estate activities (7),
- Professional scientific and technical activities (8),
- Administrative and support service activities (9).

The data providers are National Statistical Institutes and National Central Banks which collect firm-level administrative data which are used to compute the micro-aggregated indicators through a single and harmonized algorithm. Arguably, the data sources for each country are the most representative and complete (in terms of firm and industry coverage) datasets available for each country included in the CompNet data. Our data harmonization process and a rigid definition of input data ensure cross-country comparability. A detailed description of the harmonization process, variable input, and how the indicators are derived can be found in the User Guide (CompNet (2020)).

The dataset is publicly available to researchers from policy and academic institution by applying to the IWH Research Data Center.

Table A.1.1 provides information on coverage and mean values for a few basic variables reported in the raw CompNet data set. For most of our analysis we use a balanced sample of sectors and years over the period 2009-2016, which excludes the sectors construction (2), Wholesale, retail trade, repair of motor vehicles and motorcycles (3), and Accommodation and food service activities (5).

TABLE A.1.1

COMPNET DESCRIPTIVE STATISTICS						
	YEARS (1)	EXCLUDED MACRO-SECTORS (2)	CAPITAL INTENSITY (THOUSANDS) (3)	FIRM-SIZE (4)	ANNUAL AVERAGE FIRM WAGE (THOUSAND EUROS, PPP ADJUSTED) (5)	VALUE-ADDED OVER REVENUE (6)
Belgium	2003-2017	-	41.01	113.12	44.44	0.51
Czech Republic	2005-2017	-	30.65	113.77	25.42	0.31
Finland	1999-2017	-	31.75	102.54	31.68	0.40
France	2004-2016	-	38.14	142.93	39.28	0.68
Germany	2003-2016	(2), (3), (5)	81.07	86.79	31.16	0.51
Italy	2006-2016	-	34.72	85.14	33.64	0.63
Lithuania	2000-2016	-	19.59	138.57	13.15	0.33
Netherlands	2007-2017	(7)	26.02	116.75	39.38	0.39
Poland	2005-2017	-	33.28	83.39	19.90	0.32
Portugal	2004-2017	-	16.23	97.06	21.14	0.55
Romania	2005-2016	(7)	20.22	123.71	10.64	0.28
Slovakia	2000-2017	-	56.91	116.25	19.71	0.32
Spain	2008-2017	-	37.50	96.62	33.13	0.64
Sweden	2008-2016	-	39.98	101.22	42.45	0.78
Switzerland	2009-2017	-	31.56	113.12	56.58	0.54

Notes: Table A.1.1. reports coverage information and mean values for a set of basic variables included in the CompNet dataset. Columns 1 and 2 report the year and sector coverage of each country. Sectors are numbered in the following ways: Manufacturing (1), Construction (2), Wholesale, retail trade, repair of motor vehicles and motorcycles (3), Transportation and Storage (4), Accommodation and food service activities (5), Information and communication (6), Real estate activities (7), Professional scientific and technical activities (8), Administrative and support service activities (9). Column 3 shows capital over labor ratios (PPP adjusted and deflated using a deflator from Eurostat, 2005=100). Column 4 reports the number of employees. Column 5 reports the annual average firm wage (PPP adjusted and deflated using a deflator from Eurostat, 2005=100). Column 5 shows the value-added over revenue ratio. CompNet dataset.

Appendix A.2: German micro data - the AFiD Database

The Amtliche Firmendaten in Deutschland (AFiD) database includes various statistics at the firm level. The data can be accesses at the "Research Data Centers" of the Federal Statistical Office of Germany and the Statistical Offices of the German Länder. Data Request can be made at: https://www.forschungsdatenzentrum.de/en/request .

The statistics we used for our analysis are: AFiD-Modul Produkte", "AFiD-Panel Industriebetriebe", "AFiD-Panel Industrieunternehmen", "Investitionserhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden", "Panel der Kostenstrukturerhebung im Bereich Verarbeitendes Gewerbe, Bergbau und Gewinnung von Steinen und Erden", and „AFiD-Panel Strukturerhebung im Dienstleistungsbereich".

We follow Mertens (2020) in preparing the manufacturing sector data. In particular, we i) use publicly available information on the durability of capital goods (provided from the statistical offices of Germany) to construct a first capital stock for each firm that we firms' product portfolios to construct a time-consistent industry classification over the entire time span from 1995-2017. To create a consistent industry classification for the service sector, we rely on the CompNet approach used also in other countries. This uses official concordance tables, panel information on firms existing before and after changes in industry classification, and information on industry-level input mixes to construct a harmonized industry classification. Recap, that this data is the same data that underlies the CompNet results for Germany.[25]

[25] To account for measurement error, we drop the top and bottom two percent of outliers in firm sales over production inputs.

Finally, to provide an overview on the manufacturing product-level data, Table A.2.1 shows examples of product classification.

TABLE A.2.1

EXAMPLES OF INDUSTRY AND PRODUCT CLASSIFICATIONS

NACE rev. 1.1	Product code	Description
18		Manufacture of wearing apparel; dressing and dyeing of fur
1821		Manufacture of workwear
		Products
	182112410(0)	Long trousers for men, cotton (not contracted)
	182112510(0)	Overalls for men, cotton (not contracted)
	182112510(2)	Overalls for men, cotton (contracted production)
	182121350(2)	Coats for women, chemical fiber (contracted production)
27		Manufacture of basic metals
2743		Lead, zinc, and tin production
		Products
	274312300(0)	Zinc, unwrought, refined (not contracted)
	274311300(0)	Lead, unwrought, refined (not contracted)
	274311500(0)	Lead, unwrought, with antimony (not contracted)
	274328300(0)	Tin sheets and tapes, thicker than 0.2mm (not contracted)
	274328600(0)	Tin sheets and tapes, not thicker than 0.2mm (not contracted)

Notes: Table A.2.1 presents examples of the products available in our data. The reported GP2002 product codes define 6,500 distinct products at the nine-digit level from which we find 5,927 in our database and 4,194 in our final sample of firms. The last number of each product code (10^{th} position) indicates whether the product was manufactured as contracted work (2). Source: Mertens & Müller (2020).

Appendix B: Alternative European data sources

Appendix B.1: ORBIS data

The ORBIS data is provided by the Bureau Van Dijk (BVD). The ORBIS database is the largest cross-country firm-level panel, and it includes financial variables and other information of public and private firms (see Kalemli-Ozcan et al. 2015). Although it is the largest existing European firm-level panel database it suffers from several drawbacks. As firms are not obliged by law (which they are for the data underlying CompNet) to report in the ORBIS database and as regulations differ, the firm coverage in the ORBIS data is biased towards big firms belonging to manufacturing sector.

As Bajgar et al. (2020) point out, the coverage of small and medium firms is much lower back in time and increase only in recent years. This inconsistency in firm coverage, makes it particularly problematic to measure firm concentration, as concentration indices are directly affected by changes in the number of sample firms. Bajgar et al. (2020) also conclude that the ORBIS data is unsuitable for cross-country comparisons and for studying firm distributions. This is, however, precisely at the center of our study. Moreover, for understanding the (cross-country) reallocation processes we highlight in this study, having a representative and across country harmonized and comparable dataset is key.

Appendix B.2: Multiprod data

Another cross-country database is the Multiprod data from the OECD, which, similar, to CompNet, has been constructed in cooperation with national statistical institutes that provide their administrative data to the OECD. The data covers 22 countries (also outside Europe) and it provides indicators on firm performance (including productivity) starting from 2000. Although the quality of this data is high, Multiprod cannot be accessed by researchers outside of the OECD. This makes it impossible for us to use this data and also prevents reproducing any results derived from the Multiprod data. In contrast the CompNet data we built can be readily (without any costs) accessed by any researcher and our results can be easily reproduced using our codes.

Appendix C: Alternative concentration measures

Appendix C.1: Top 10 share and HHI comparison

In our analysis, we focus on the HHI as our concentration measures (yet we replicate main regression results also for the revenue share of the largest ten firms). We do this due to the nice decomposition features of the HHI. In this section, we show that the HHI and top firm revenue share are highly correlated with each other. We focus here on all available sector-year observations in the data, but results hold also for our balanced sample of years and sectors.

Figure C.1.1 confirms that HHI and Top10 revenue share are highly positively correlated. Excluding one outlier, the points of the scatter plots are almost ordered along one straight line.

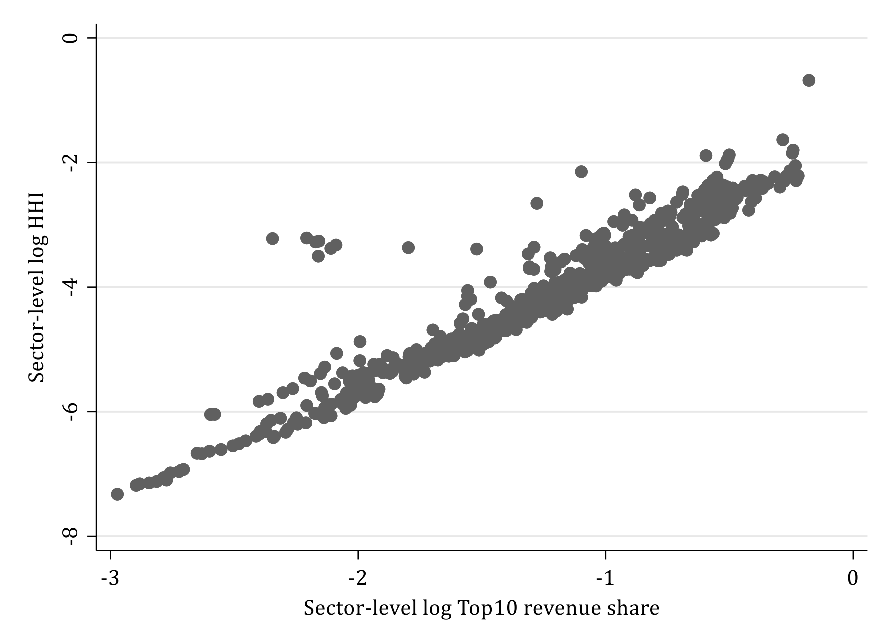

Figure C.1.1 - Correlation between logged sector-level revenue shares of the 10 largest firms and sector-level HHIs. CompNet dataset. All available sectors and years. Set of countries we use throughout our study.

Similarly, Table C.1.1 shows pairwise correlations between the HHI and the Top10 firm revenue share at the sector level, both in levels and first differences. Again, there is a strong positive correlation between both concentration measures.

TABLE C.1.1

CORRELATION BETWEEN HHI AND TOP 10 SHARE

	HHI	HHI first diff
Top10 Share	0.7986	
Top10 Share first diff		0.5598

Notes: Table C.1.1 shows the pairwise correlation of sector-level HHIs and revenue shares of the 10 largest firms, both in levels and first differences. CompNet dataset. All available sectors and years. Set of countries we use throughout our study.

Appendix C.2: Weighted vs. unweighted HHIs

In our analysis, we use non-population weighted (sample) concentration measures, whereas for all other variables, our CompNet data only provides population weighted measures. Our choice for non-population weighted concentration measures results from many missing values for population weighted HHIs in the data. Most notably, Germany does only report sample HHIs.[26]

However, this is not much of a concern to us because population-weighted and sample HHIs are highly correlated in the CompNet data. This holds for levels and changes. Over time, both HHI measures display almost identical patterns. Ultimately, this reflects the high and representative coverage of the firm-level data underlying the CompNet data.

Figures C.2.1 and C.2.2 illustrate the similarity between sample and population weighted HHIs using sector and country level data. Notably, Figure C.2.2 does not only include the set of macro-sectors we focus on in our main analysis. Instead, it includes all available macro-sectors for each country. This is because due to several

[26] This is a result of the disclosure routine of the CompNet data collection protocols.

missing values of population weighted HHIs at the macro-sector, one cannot aggregate population weighted macro-sectors to the country level without loosing a disproportional number of observations.

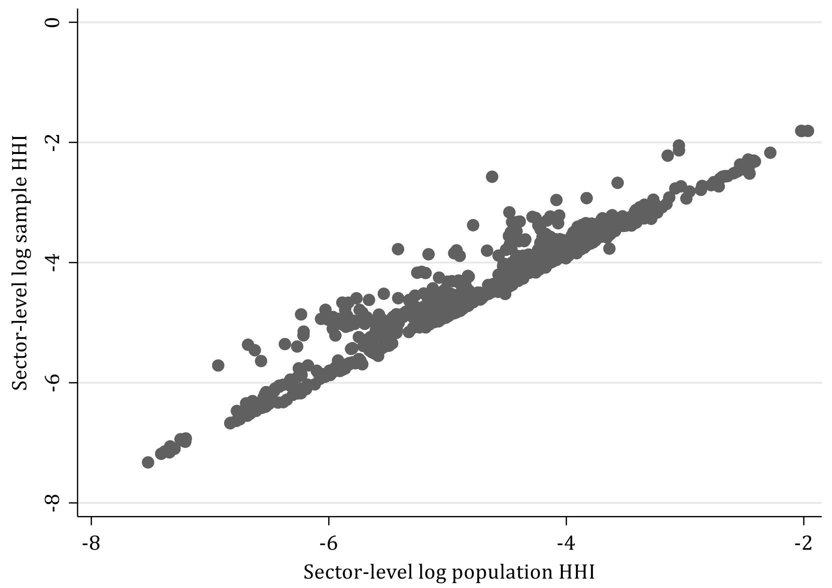

Figure C.2.1 - Correlation between logged population weighted and non-weighted HHIs at the sector level. CompNet dataset. All available sectors and years. Set of countries we use throughout our study.

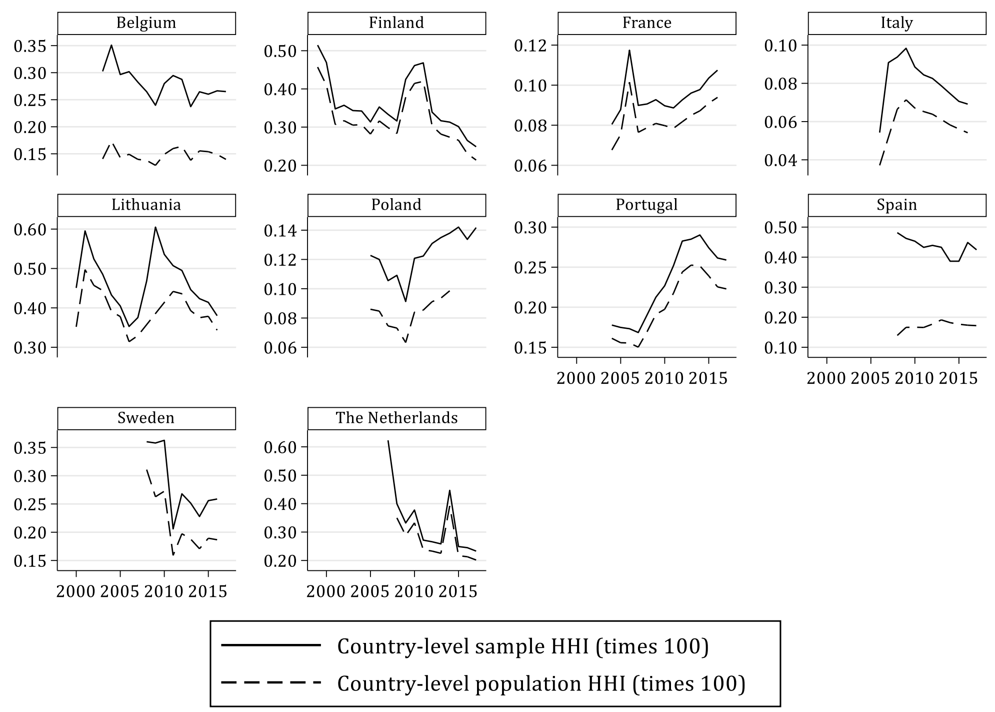

Figure C.3 - Correlation between logged population weighted and non-weighted HHIs at the country level. CompNet dataset. All available sectors and years. Set of countries we use throughout our study which report population weighted an sample HHIs.

Appendix D: Estimation of markups in CompNet

Markups are estimated using the approach by De Loecker & Warzynski (2012). De Loecker & Warzynksi (2012) showed that markups can be derived from firms' first order conditions as the wedge between the output elasticity of a flexible input and its invers share in output:

(D.1)
$$\mu_{it} = \alpha_{it}^{M} * \frac{P_{it}Q_{it}}{P_{it}^{M}M_{it}}$$

where μ_{it} denotes the markup, α_{it}^{M} is the output elasticity of intermediate inputs, and $\frac{P_{it}Q_{it}}{P_{it}^{M}M_{it}}$ is the inverse of the share of intermediate input expenditures in revenues. i and t denote the firm and time dimension. We chose intermediate inputs as our flexible variable as recent research showed that using labor expenditures, or the sum of labor and intermediate input expenditures will not give a true markup measure, even if labor and intermediates are truly flexible inputs (e.g Mertens (2020)). This is because wedges between output elasticities of labor and the invers share of labor expenditures in sales yield a product of product markups and wage markdowns (labor market power):

(D.2)
$$\mu_{it}\gamma_{it} = \alpha_{it}^{L} * \frac{P_{it}Q_{it}}{P_{it}^{L}L_{it}},$$

where α_{it}^{L} is the output elasticity of labor and $P_{it}^{L}L_{it}$ denotes the wage bill. γ_{it}denotes the wage markdown (labor market power). Hence, equation (D.2) can only be used to estimate markups if labor markets are competitive. For more discussion, we refer to Mertens (2020).

We derive output elasticities from estimating a production function for each two-digit industry within each country separately. We collect several specifications of the production function in the CompNet dataset. For our analysis here we focus on a translog production function estimated by OLS because control function approaches provided rather instable results with partly huge output elasticities exceeding unity for individual inputs in some countries.[27]

Specifically, the production on which we base our markup estimates is:

$$\text{(D.2)} \quad q_{it} = \beta_l l_{it} + \beta_m m_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} + \beta_{lm} l_{it} m_{it} + \beta_{km} k_{it} m_{it} + \beta_{lkm} l_{it} k_{it} m_{it} + \omega_{it} + \varepsilon_{it},$$

where m_{it}, l_{it}, and k_{it} denote logged values of intermediates, labor, and capital, deflated by industry-level deflators supplied from Eurostat.[28] q_{it} is logged gross output, also deflated by an industry-level deflator, ω_{it} is total factor productivity and ε_{it} is an i.i.d error term.[29]

Notably, the CompNet data does not provide any production function specifications controlling for firm-specific price variation in estimating the production function. This is because it is virtually impossible to conduct a harmonized production function estimation across 15 (and more) including firm-specific price data, which is only available in a few selected countries. To create comparable results, the CompNet data therefore does not include any such specifications. For market power studies accounting for firm-specific price data, see De Loecker, Goldberg, Khandelwal, & Pavcnik (2016) and Mertens (2020).

[27] Yet, our results are robust to using alternative markup estimates from alternative production function specifications. Particularly, markups based on different specifications (including control function approaches) are stable over time. Only aggregate levels depart, due to outliers in several country-industry pairs.

[28] Because intermediate input deflators are often missing, we use value-added deflators to deflate intermediate inputs.

[29] The assumption when estimating (D.3) by OLS is that unobserved productivity is uncorrelated with production inputs and q_{it}. Again, our results are robust to using markups from a control function approach in the spirit of Wooldridge (2009), which are also contained in the CompNet data.

Appendix E: Productivity-size premiums for the balanced sample

Table E.1 and E.2 replicate our estimation on productivity-size premiums for our balanced set of sectors, years, and countries. We exclude The Netherlands and Romania due to missing values in the joint distributions we use (this is a result of the disclosure routine). As shown, the results are closely in line with the corresponding Figure 2 of the main text.

TABLE E.1

PRODUCTIVITY-SIZE-PREMIUM BY COUNTRY,
BALANCED SAMPLE OF SECTORS AND YEARS

	Europe	Belgium	Czech Republic	Finland	France	Germany	Italy	Lithuania	Poland	Portugal	Slovakia	Spain	Sweden	Switzerland
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$size\ decile_{J,t}$	0.017***	0.006	0.013***	0.0113***	0.007***	0.0117***	0.0219***	0.0413***	0.0068	0.024***	0.0082	0.031***	0.021***	0.005
	(0.0026)	(0.0036)	(0.0037)	(0.0033)	(0.0029)	(0.0049)	(0.0035)	(0.086)	(0.0065)	(0.004)	(0.0083)	(0.0038)	(0.0039)	(0.006)
$Capital\ Intensity_{jt}$	0.175***	0.216***	0.181***	0.124***	0.294***	0.179***	0.195***	0.128**	0.194***	0.191***	0.204***	0.229***	0.123***	0.110***
	(0.0141)	(0.046)	(0.0242)	(0.0205)	(0.0219)	(0.0539)	(0.0363)	(0.0451)	(0.0385)	(0.0332)	(0.0435)	(0.0288)	(0.0209)	(0.0162)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Industry-country FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	26,321	1,048	1,825	1,088	3,360	2,986	3,129	629	2,525	1,632	754	2,750	2,933	1,662
# of Sectors	47	20	35	20	43	43	44	11	38	28	16	38	40	44
R-squared	0.935	0.890	0.886	0.890	0.928	0.920	0.923	0.814	0.878	0.894	0.793	0.874	0.832	0.813

Notes: TableE.1 reports results from estimating equation (6) of the main text separately by countries. The Netherlands and Romania due for missing information (as a results of strict disclosure criteria). The sample is based on our balanced set of sectors and years and restricted to 2009-2016. Standard errors are clustered at the sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset

Table E.2

SIZE-PREMIUM ON PRODUCTIVITY BY MACRO SECTORS

	Manufacturing	Transportation and storage	Information and communication	Real estate	Professional, scientific and Technical Activities	Administrative and support service activities
	(1)	(2)	(3)	(4)	(5)	(6)
$size\ decile_{j,t}$	0.023***	-0.0062*	0.0255***	0.0175	0.0123**	-0.0042
	(0.0025)	(0.0024)	(0.006)	(-)	(0.0037)	(0.0068)
$Capital\ Intensity_{jt}$	0.214***	0.133**	0.154**	0.163	0.0741***	0.153***
	(0.0227)	(0.036)	(0.0502)	(-)	(0.0184)	(0.0296)
Time FE	YES	YES	YES	YES	YES	YES
Country-Industry FE	YES	YES	YES	YES	YES	YES
Observations	14,762	1,976	2,235	660	3,388	3,300
# of Sectors	22	5	6	1	7	6
R-squared	0.950	0.942	0.867	0.926	0.871	0.948

Notes: TableE.2 reports results from estimating equation (6) separately by macro-sectors. The sample is based on our balanced set of sectors and years and restricted to 2009-2016. Standard errors are clustered at the sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset.

Appendix F: Robustness tests for our concentration-productivity regression analysis

This section provides a series of additional results and robustness tests for our regression analysis of section 5.2. Appendix F.1 replicates our main analysis using a total factor productivity (TFP) measure instead of labor productivity. Appendix F.2 replicates our main regressions using between-industry instead of within-industry variation for identification (i.e. we exclude sector fixed effects and only include year and country fixed effects). Finally, Appendix F.3 reruns our main regressions using lagged values in dependent variables, which accounts for potential reverse causality. We validate our results across all these robustness tests.

Appendix F.1: Using a semi-parametric TFP measure

Tables F.1.1-F.1.8 replicate Tables 8-11 from the main text using TFP as productivity measures instead of labor productivity. We estimate TFP from a Cobb-Douglas production function using OLS. Although we also include more sophisticated production function specifications in the CompNet (including TFP derived from control function approaches) we use the OLS-Cobb-Douglas specification because it provides the largest coverage and most robust estimates of the production function.[30] We also exclude the control for capital over labor ratios as TFP measures account for changes in the production factor mix by itself. This also increases the number of available observations.

[30] Due to control function approaches being much more demanding, TFP is sometimes missing at the country-industry-year-level for these specifications due to countries' disclosure rules requiring a certain number of observations for producing results. Additionally, the control function approaches in the CompNet data are not producing meaningful production functions in every country-industry-pair, which results from a low observation count in many country-industry-pairs. Notably, we still use the Markup estimates from the translog production function as there are no industry-level aggregate markups derived from Cobb-Douglas production functions in the CompNet data. This because the Cobb-Douglas production functions impose strong restrictions on the variability of markups between firms due to imposing industry-specific and time-constant output elasticities.

Technically there are several issues with using TFP decompositions. First, ideally one would like to use quantity-based output weights, which are not observed in the data. Second, on the one hand, to recover an aggregate productivity index that is defined as aggregate output divided by aggregate inputs, one should ideally use non-logged TFP measures. Otherwise, the Olley-Pakes decomposition will not recover such an aggregate productivity index.[31] Yet, changes in TFP-levels cannot be easily compared between industries as TFP is derived from industry specific production functions. Therefore, some sectors have higher levels of TFP by design. Estimating an average coefficient across sectors, as we do, will then be affected by the level differences in TFP between sectors that results from the different production functions for each country-industry-pair. This can also not be addressed by taking logs and focusing on percentage changes, because the covariance term can be negative.

These drawbacks of the TFP as a productivity are exactly why we focus on labor productivity in the main text. Yet, as we show below, even when using TFP, our results are qualitatively identical to the ones for the labor productivity specification of the main text.

Table F.1 shows again a strong positive association between concentration and productivity, which is driven by a positive link between industry HHIs and industry-level allocative efficiency. Again, this holds after including the average firm size and markups as controls and markups are again statistically insignificant.

Tables F.3 and F.5 shows that when conducting our analysis separately by countries and sectors, we find again a robust association between concentration and allocative efficiency that holds across almost all countries and sectors of our data.

[31] This is because the sum of weighted firm-level log TFP is not equal to the log of total output divided by total inputs.

Finally, Table F.7 shows that using the revenue share of the ten largest firms as alternative concentration measure does not affect our results.

TABLE F.1.1

CONCENTRATION AND NON-LOGGED TOTAL FACTOR PRODUCTIVITY, 2-DIGIT SECTOR ANALYSIS									
	HHI_{jt} (1)	HHI_{jt} (2)	HHI_{jt} (3)	HHI_{jt} (4)	HHI_{jt} (5)	HHI_{jt} (6)	HHI_{jt} (7)	HHI_{jt} (8)	HHI_{jt} (9)
$Aggregate\ TFP_{jt}$	0.088**	0.078**	0.080**						
	(0.036)	(0.030)	(0.031)						
$Within-TFP_{jt}$				-0.049	-0.060	-0.068			
				(0.036)	(0.044)	(0.043)			
$Between-TFP_{jt}$							0.159***	0.150***	0.154***
							(0.055)	(0.050)	(0.050)
$log(Avr.Firm\ Size_{jt})$			5.147***			5.125***			5.188***
			(1.854)			(1.848)			(1.854)
$log(Aggregate\ Markup_{jt})$		3.454	2.814		4.501*	3.894		3.241	2.588
		(2.170)	(2.102)		(2.601)	(2.554)		(2.119)	(2.051)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	6,422	6,422	6,422	6,422	6,422	6,422	6,422	6,422	6,422
# of sectors	46	46	46	46	46	46	46	46	46
R-squared	0.771	0.772	0.781	0.769	0.771	0.779	0.773	0.774	0.783

Notes: Table F.1.1 shows regression result from estimating equation (7) using aggregate total factor productivity (columns 1-3), the corresponding within-firm component (columns 4-6), and corresponding allocative efficiency component (columns 7-9) as explanatory variables. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet data.

TABLE F.1.2

CONCENTRATION AND TFP 2-DIGIT SECTOR ANALYSIS			
	$Aggregate\ TFP_{jt}$ (1)	$Within-firm\ TFP_{jt}$ (2)	$Between-firm\ TFP_{jt}$ (3)
Belgium	0.0243 (0.0162)	0.00757 (0.0499)	0.0312* (0.0182)
Czech Republic	-0.118 (0.304)	-0.0451 (0.338)	-0.332 (1.071)
Finland	3.923*** (1.194)	1.833* (1.034)	2.954*** (0.843)
France	0.1126** (0.060)	-0.110 (0.0970)	0.178** (0.0742)
Germany	1.287 (0.883)	-1.303** (0.538)	1.799** (0.687)
Italy	0.00306 (0.0191)	-0.0215 (0.0271)	0.0269 (0.0287)
Lithuania	1.779 (1.933)	-4.774 (2.857)	8.460** (3.810)
Netherlands	1.234 (0.928)	1.721* (0.946)	1.477 (1.334)
Poland	0.979 (1.121)	-0.138 (0.687)	2.413* (1.385)
Portugal	0.109 (0.409)	-0.638 (0.642)	0.265 (0.541)
Romania	-4.256 (4.064)	-9.014 (6.378)	7.858 (6.009)
Slovakia	1.436 (1.449)	-0.0516 (0.969)	3.815 (2.513)
Spain	0.189 (0.138)	0.132 (0.378)	0.189* (0.0991)
Sweden	-0.0849* (0.0441)	-0.162** (0.0678)	-0.0688 (0.0879)
Switzerland	1.655*** (0.448)	0.624 (0.863)	1.986*** (0.572)

Notes: Table F.1.2 shows regression coefficients on from estimating equation (7) separately by countries when using logged average firm size and logged industry-level markups as control variables and when using TFP as productivity measure. Column 1, 2, and 3 respectively show coefficients when using industry-level allocative aggregate productivity, within-firm productivity, and allocative efficiency as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset.

TABLE F.1.3

CONCENTRATION AND TFP
2-DIGIT SECTOR ANALYSIS

	$Aggregate\ TFP_{jt}$ (1)	$Within-firm\ TFP_{jt}$ (2)	$Between-firm\ TFP_{jt}$ (3)
Manufacturing	0.545 (0.456)	-0.298 (0.376)	1.981*** (0.692)
Transportation, storage	0.0252 (0.0469)	-0.190 (0.102)	0.117 (0.0831)
Information, communication	0.114 (0.0588)	0.0128 (0.0959)	0.179** (0.0597)
Real estate	-0.001 (-)	0.0108 (-)	-0.0146 (-)
Professional, scientific, technical activities	0.107 (0.052)	-0.0591 (0.0417)	0.144* (0.0679)
Administrative, support service activities	0.0219*** (0.00483)	0.001 (0.0092)	0.0379** (0.0105)
High-tech, knowledge intensive	0.100** (0.0425)	-0.0746 (0.0580)	0.178*** (0.0606)
Low-tech, not knowledge intensive	0.0288 (0.0220)	-0.0470 (0.064)	0.0793 (0.0699)

Table F.1.3 shows regression coefficients from estimating equation (7) separately by sectors when using total factor productivity as explanatory variable and controlling for logged industry average firm size and logged industry-level markups. Column 1, 2, and 3 respectively show coefficients when using industry-level aggregate TFP, within-firm TFP, and allocative efficiency as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and countries. All available industries and years. CompNet data.

* Standard errors could not be estimated for the Real Estate sector as this only consist of one industry (one cluster in our estimation.

TABLE F.1.4

CONCENTRATION AND PRODUCTIVITY 2-DIGIT SECTOR ANALYSIS						
	$Top10_{jt}$ (1)	$Top10_{jt}$ (2)	$Top10_{jt}$ (3)	$Top10_{jt}$ (4)	$Top10_{jt}$ (5)	$Top10_{jt}$ (6)
$Aggregate\ TFP_{jt}$	0.144*** (0.030)	0.140*** (0.031)				
$Within - TFP_{jt}$			-0.0448 (0.0473)	-0.0644 (0.0513)		
$Between - TFP_{jt}$					0.237*** (0.0406)	0.237*** (0.0397)
$log(Avr.Firm\ Size_{jt})$		8.147*** (1.806)		8.060*** (1.785)		8.208*** (1.816)
$log(Aggregate\ Markup_{jt})$		2.259 (2.718)		3.888 (3.002)		2.159 (2.658)
Time FE	YES	YES	YES	YES	YES	YES
Country-industry FE	YES	YES	YES	YES	YES	YES
Observations	5,846	5,846	5,846	5,846	5,846	5,846
# of sectors	45	45	45	45	45	45
R-squared	0.938	0.941	0.938	0.941	0.939	0.942

Notes: Table F.1.4 displays regression result from estimating equation (7) using the share of the 10 largest firms in revenue as dependent variable and aggregate TFP (column 1,2), within-firm TFP (column 3,4), allocative efficiency (column 5,6) as explanatory variables. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet dataset

Appendix F.2: Identifying the coefficients from cross-sectional variation

TABLE F.2.1

CONCENTRATION AND PRODUCTIVITY 2-DIGIT SECTOR ANALYSIS									
	HHI_{jt} (1)	HHI_{jt} (2)	HHI_{jt} (3)	HHI_{jt} (4)	HHI_{jt} (5)	HHI_{jt} (6)	HHI_{jt} (7)	HHI_{jt} (8)	HHI_{jt} (9)
$Aggregate\ producitivity_{jt}$	0.031***	0.030***	0.028***						
	(0.005)	(0.005)	(0.003)						
$Within-firm\ productivity_{jt}$				0.027***	0.026***	0.025***			
				(0.006)	(0.006)	(0.006)			
$Between-firm\ productivity_{jt}$							0.085***	0.084***	0.074***
							(0.016)	(0.016)	(0.013)
$Capital\ Intensity_{jt}$	-0.003*	-0.003	-0.002*	-0.002	-0.002	-0.001	-0.001	-0.001	-0.000
	(0.002)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)
$log(Avr.Firm\ Size_{jt})$			3.763***			3.979***			3.456***
			(0.606)			(0.674)			(0.605)
$log(Aggregate\ Markup_{jt})$		0.374	0.054		0.659	0.274		0.427	0.151
		(0.457)	(0.361)		(0.488)	(0.485)		(0.431)	(0.348)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	7,839	7,839	7,839	7,839	7,839	7,839	7,839	7,839	7,839
# of Clusters	47	47	47	47	47	47	47	47	47
R-squared	0.207	0.208	0.291	0.161	0.162	0.256	0.247	0.248	0.317

Notes: Table F.2.1. reports regression results from estimating equation (7) using aggregate productivity (column 1-3), within-firm productivity (column 4-6), and allocative efficiency (columns 7-9) as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet data.

Appendix F.2: Using lagged productivity as explanatory variable

TABLE F.3.1

CONCENTRATION AND LAGGED PRODUCTIVITY,
2-DIGIT SECTOR ANALYSIS

	HHI_{jt} (1)	HHI_{jt} (2)	HHI_{jt} (3)	HHI_{jt} (4)	HHI_{jt} (5)	HHI_{jt} (6)	HHI_{jt} (7)	HHI_{jt} (8)	HHI_{jt} (9)
$Aggregate\ producitivity_{jt-1}$	0.026***	0.025***	0.027***						
	(0.006)	(0.006)	(0.006)						
$Within-firm\ productivity_{jt-1}$				-0.007	-0.010	-0.007			
				(0.007)	(0.008)	(0.007)			
$Between-firm\ productivity_{jt-1}$							0.070***	0.070***	0.070***
							(0.022)	(0.023)	(0.001)
$Capital\ Intensity_{jt-1}$	-0.002	-0.002	-0.002	-0.0009	-0.0006	0.002	-0.002	-0.002	-0.002
	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)
$log(Avr.Firm\ Size_{jt-1})$			4.814**			4.511**			4.636**
			(1.919)			(1.905)			(1.754)
$log(Aggregate\ Markup_{jt-1})$		0.867	0.225		3.614	3.048		-0.341	-0.826
		(1.670)	(1.652)		(2.352)	(2.307)		(1.495)	(1.500)
Time FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Country-Industry FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	5,872	5,872	5,872	5,872	5,872	5,872	5,872	5,872	5,872
# of Clusters	46	46	46	46	46	46	46	46	46
R-squared	0.778	0.778	0.787	0.770	0.772	0.780	0.793	0.793	0.802

Notes: Table F.3.1. displays regression results from estimating equation (7) using 1-year lagged aggregate productivity (column 1-3), 1-year lagged within-firm productivity (column 4-6), and 1-year lagged allocative efficiency (columns 7-9) as explanatory variable. Standard errors are clustered at sector level. Significance: *10 percent, **5 percent, ***1 percent. All available industries and years. CompNet data.

Appendix G: Quantifying the within- and between-firm components of the productivity-concentration link

Table G.1 shows results from regression industry-level productivity and the corresponding within- and between-firm productivity decompositions terms on log HHIs (reversing equation (7) from the main text) while adding all our control variables industry capital-labor ratios, average firm size, industry markups). As the coefficients from the within-firm and between-firm (allocative efficiency) component regressions add up to the coefficient from the regression for aggregate productivity, one can calculate the separate share of the concentration-productivity association that results from a positive association between concentration and within-firm productivity and between-firm productivity. This is reported in columns 4 and 5 of Table G.1. Hence, 99% of the association between concentration and productivity is explained by a positive association between concentration and allocative efficiency.

TABLE G.1

CONCENTRATION AND LAGGED INTANGIBLE FIXED ASSETS PER EMPLOYEE, 2-DIGIT SECTOR ANALYSIS					
	$Aggregate\ productivity_{jt}$	$Within-firm\ productivity_{jt}$	$Allocative\ efficiency_{jt}$	Contribution of within-firm component	Contribution of allocative efficiency component
	(1)	(2)	(3)	(4)	(5)
$log(HHI_{jt})$	8.579***	0.0949	8.485***	1%	99%
	(1.764)	(1.432)	(1.902)		
$Capital\ Intensity_{jt}$	0.0608*	0.0439**	0.0170		
	(0.0342)	(0.0205)	(0.0155)		
$log(Avr.Firm\ Size_{jt})$	-12.91***	-8.349***	-4.561		
	(3.954)	(3.006)	(3.533)		
$log(Aggregate\ Markup_{jt\text{-}}$	84.82**	42.36***	42.46*		
	(32.81)	(12.63)	(23.42)		
Time FE	YES	YES	YES		
Country-Industry FE	YES	YES	YES		
Observations	6,364	6,364	6,364		
# of Clusters	47	47	47		
R-squared	0.931	0.932	0.932		

Notes: Table G.1. reports regression results from regression industry-level productivity and its within- and between-firm components on logged industry-level HHIs (reversing equation (7) of the main text). Column 1-3 show associated results. Columns 4 and 5 derive the implied contribution of within-firm and allocative efficiency (between-firm) productivity to the positive association between industry-level productivity and concentration. Standard errors are clustered at the industry level. All available industries and years. CompNet data.

Appendix H: Additional results on European concentration and productivity dynamics

This section shows additional results on European concentration and productivity dynamics. Appendix H.1 shows that if we exclude Germany from our sample, the increase in European concentration reverses and becomes a decrease in European concentration. This further underlies the key role of Germany in shaping aggregate concentration patterns in Europe. Appendix H.2 replicates the within-/between-HHI-decomposition results but further separates the within-component into the unweighted mean and a scaling factor. Appendix H.3 extends our calculates the contribution

Appendix H.1: European concentration with and without Germany

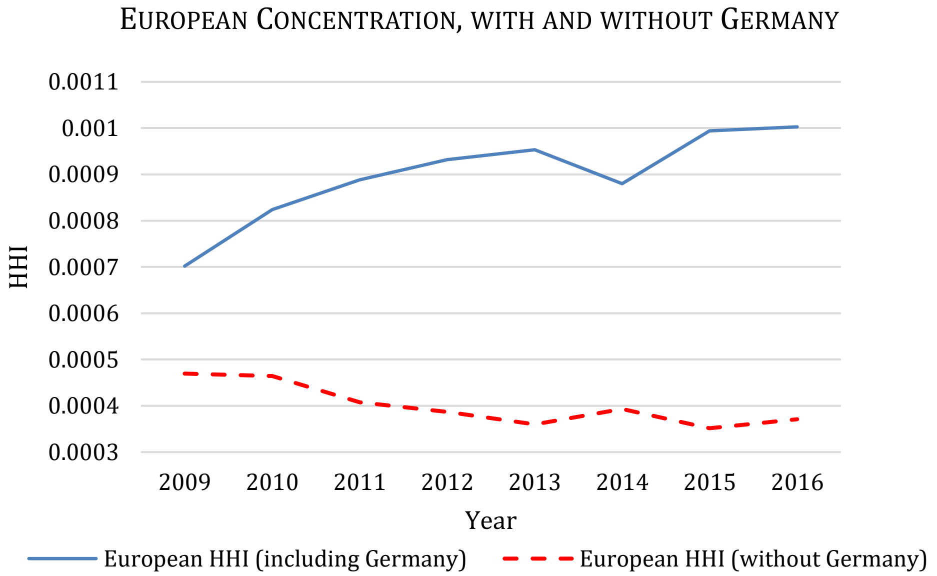

FIGURE H.1.1 – European firm concentration. The blue solid line shows the European Hirschman-Herfindahl index for all sectors and countries of our balanced sample. The red dashed line excludes Germany from the sample. Balanced sample for 2009 to 2016. CompNet dataset.

Appendix H.2: HHI within-between decomposition including a separate scaling term

The HHI-within-between-decomposition of the main text can be further separated:

$$HHI_t = N * \bar{s} * \overline{HHI} + cov(HHI_{nt}, s_{nt})$$

$$= \overline{HHI} + \overline{HHI}(N\bar{s} - 1) + cov(HHI_{nt}, s_{nt}). \tag{H.2.1}$$

The first term of equation (H.2.1) is the unweighted mean of the country (sector) level HHI, while the last term is the covariance between the weight s_{nt} (squared revenue shares) and the country (sector) level HHI. The term in the middle is a scaling component that accounts for the fact that aggregating the HHI across two entity must yield a lower aggregate HHI (because the market size increased). The scaling component rescales the unweighted mean HHI ($\overline{HHI}$) to be of the same order of magnitude as the aggregate HHI (HHI_t). Note that as the sum of weights converges to 1, the term in the middle vanishes. This point is reached when there is only one entity (i.e. only one country/sector and there is nothing to be aggregated).

In the main text, we interpret $\overline{HHI} + \overline{HHI}(N\bar{s} - 1)$ as the within-change in the aggregate HHI and conclude that most of the changes in the aggregate HHI result from a reallocation of market shares between countries (sectors). The standard Olley-Pakes decomposition interprets the unweighted mean as the within-component as it does not include a scaling component (because there, the weights sum up to unity).

Table H.2.1 replicates the decomposition but with separating the within component into the unweighted mean HHI and the rescaling component. As can be clearly seen, without rescaling the unweighted mean HHI, its level is far above the aggregate HHI.

Nevertheless, changes in the unweighted mean HHI do still not contribute to the rise in concentration. Hence, even if we treat the unweighted mean as the within-firm component, we still conclude that the rise of European concentration is driven by reallocation processes between countries and sectors. Note that for the country-decomposition, the contribution of the scaling factor is rather large. This reflects that there is an increasing dispersion in market shares. between countries.

TABLE H.2.1

HHI-DECOMPOSITION,
WITHIN VS. BETWEEN COUNTRY AND ONE-DIGIT SECTOR CHANGES

		Country-level decomposition			Sector-level decomposition		
Year	Aggregate HHI (times 100) (1)	Unweighted mean country level (times 100) (2)	Scaling factor country level (times 100) (3)	Between-country (times 100) (4)	Unweighted mean sector level (times 100) (5)	Scaling factor sector level (times 100) (6)	Between-sector (times 100) (7)
2009	0.070	0.599	-0.503	-0.026	0.353	-0.188	-0.094
2010	0.082	0.660	-0.554	-0.024	0.336	-0.176	-0.078
2011	0.089	0.641	-0.536	-0.017	0.311	-0.161	-0.061
2012	0.093	0.642	-0.535	-0.014	0.319	-0.166	-0.059
2013	0.095	0.595	-0.492	-0.007	0.340	-0.177	-0.067
2014	0.088	0.618	-0.514	-0.016	0.334	-0.176	-0.069
2015	0.099	0.586	-0.486	-0.001	0.310	-0.166	-0.044
2016	0.100	0.583	-0.485	0.002	0.347	-0.192	-0.053
Percentage contribution 2009-2016	42.87%	-22.29%	25.82%	39.34%	-9.02%	-6.05%	57.94%

Notes: Table H.2.1 shows the HHI decomposition from equation (H.2.1) at the country (columns 2-4) and sector (columns 5-7) level. Column 1 shows the level of the European HHI, while columns 2-7 show the levels of the unweighted mean, rescaling, and between components that sum up to the aggregate HHI. The last row shows the percentage change of the aggregate HHI in column 1 over the entire time span (2009-2016). Columns 2-7 of the last row display the percentage point contribution of the unweighted mean, rescaling, and between terms to the entire decline in the HHI. Balanced sample of countries and sectors. CompNet Dataset.

Appendix H.3: HHI contribution for top and bottom country-sector pairs

Table H.3.1 shows the contribution of individual country-sector pairs to the European HHI. Germany's manufacturing sector contributes by far the most to aggregate concentration (column 1). It also experiences the largest change in contribution (column 3).

Although contributing by far less (due to its small size), the ICT sector also displays a high contribution, compared to other sectors. Yet, it also experienced the largest decrease in contribution to the aggregate HHI (column 5). Overall, Table H.3.1 demonstrates the key role of the German manufacturing sector in explaining European concentration. That is also why excluding Germany from the sample completely changes the patterns of the European HHI (see Appendix H.1).[32]

TABLE H.3.1

COUNTRY-SECTOR CONTRIBUTION TO EUROPEAN HHI 2009-2016, LEVELS AND CHANGES

Top 5 (average 2009-2016) (1)	Bottom 5 (average 2009- 2016) (2)	Top 5 changes (2009-2016) (3)	Bottom 5 changes (2009-2016) (4)
Germany -Manufacturing (74.98%)	Lithuania – Real estate (0.00002%)	Germany – Manufacturing (17.66%)	Spain – ICT (-5.50%)
Spain – ICT (2.79%)	Lithuania – Professional, scientific, technical activities (0.0004%)	Czech Republic – Manufacturing (0.56%)	Spain – Manufacturing (-2.64%)
Germany – ICT (2.66%)	Slovakia – Real estate (0.0004%)	France – Transportation and storage (0.27%)	Germany – ICT (-2.37%)
Spain – Manufacturing (2.42%)	Belgium – Real estate (0.0005%)	Slovakia – Manufacturing (0.18%)	Italy – ICT (-1.75%)
France – ICT (1.99%)	Lithuania – Administrative, support service activities (0.0007%)	Germany– Administrative, support service activities (0.12%)	France – ICT (-1.34%))

Notes: Table H.3.1 shows the contribution of each country-sector pair of our sample to the European HHI, measured by the percentage share of the European HHI that is accounted for by each country-sector pair. Columns 1 and 2 show the top and bottom contributors, respectively. Column 3 and 4 report the country-sector pairs with the largest change in HHI contribution to the European HHI. Balanced samples of countries and sectors, 2009-2016. CompNet dataset.

[32] We also looked into which sectors gained the most in terms of sales market shares and found that between 2009 and 2016, the largest increase in market shares were experienced by the German Administrative support service activities sector (+0.86%), the Polish manufacturing sector (+0.80%), and the German manufacturing sector (+0.79%).

Appendix J: Classification of technology and knowledge intensity

TABLE J.1

INDUSTRIES ACCORDING TECHNOLOGICAL AND KNOWLEDGE INTENSITY

Industry classification	Nace 2-digit industry	
High-medium technology and knowledge intensive services	20-21	Manufacture of basic pharmaceutical products and pharmaceutical preparations; Manufacture of chemicals and chemical products
	26 - 30	Manufacture of computer, electronic and optical products; Manufacture of electrical equipment; Manufacture of machinery and equipment n.e.c. ; Manufacture of motor vehicles, trailers and semi-trailers; Manufacture of other transport equipment
	50-51	Water transport; Air transport;
	58-63	Publishing activities: Motion picture, video and television program production, sound recording and music publish activities; Programming and broadcasting activities; Telecommunications; computer programming, consultancy and related activities; Information service activities
	64-66	Financial and insurance activities
	69-75	Legal and accounting activities; Activities of head offices, management consultancy activities; Architectural and engineering activities, technical testing and analysis; Scientific research and development; Advertising and market research; Other professional, scientific and technical activities; Veterinary activities
	78,80,84-93	Employment activities; Security and investigation activities; Public administration and defense, compulsory social security ; Education, Human health and social work activities; Arts, entertainment and recreation.
Medium-low technology and less knowledge intensive services	19	Manufacture of coke and refined petroleum products
	22-25	Manufacture of rubber and plastic products; Manufacture of other non-metallic mineral products; Manufacture of basic metals; Manufacture of fabricated metals products, excepts machinery and equipment
	33	Repair and installation of machinery and equipment
	10-18	Manufacture of food products, beverages, tobacco products, textile, wearing apparel, leather and related products, wood and of products of wood, paper and paper products, printing and reproduction of recorded media
	31-32	Manufacture of furniture; Other manufacturing
	45-47,49,52-53,55-56	Wholesale and retail trade; Repair of motor vehicles and motorcycles (section G); Land transport and transport via pipelines; Warehousing and support activities for transportation; Postal and courier activities; Accommodation and food service activities (section I)
	68,77,79,81,82	Real estate activities; Rental and leasing activities; Travel agency, tour operator reservation service and related activities; Services to buildings and landscape activities; Office administrative, office support and other business support activities;
	94-99	Activities of membership organization; Repair of computers and personal and household goods; Other personal service activities; Activities of households as employers of domestic personnel; Undifferentiated goods- and services-producing activities of private households for own use; Activities of extraterritorial organizations and bodies

Notes: Table J.1 shows the classification of NACE Rev.2 2-digit sectors according to technology and knowledge intensity. The classification is from Eurostat.

Appendix K: Product markups in Germany's manufacturing sector

Mertens (2020) estimates product markups for the German manufacturing sector using a production function (translog) approach that controls for firm-specific output and input price variation and corrects for the well-known simultaneity biases from firms' flexible input decisions.

In a nutshell, the approach i) uses product price information (observed in the German manufacturing sector data) to construct a firm-specific price index that is used deflate observed firm revenues and to purge it from output price variation, ii) uses output price and market share information to control for unobserved firm input price variation (by assuming that output prices are informative about input prices), and iii) corrects for the simultaneity biases from firms' flexible input decisions using a control function approach as in Wooldridge (2009).

We refer to Mertens (2020) for a full description of the approach. Here, we report the results for German manufacturing sector markups and compare them with CompNet estimates derived from a translog production function that compared to Mertens (2020) ignores firm specific price variation, various potential productivity shifters (like export status), and the described simultaneity biases.

Although this likely leads to biased product markups, we expect that changes over time are less affected by this bias as the coefficients of the translog production function are constant over time.[33]

Figure K.1 compares both markup estimates, our simple CompNet data estimates and the more sophisticated estimation routine in Mertens (2020) (using cost weights for both). As expected, levels differ somewhat, although both being,

[33] There might still be a bias in the time-variation of markups due to output elasticities of the production function being time-varying. Yet, we expect this to be much smaller compared to the level differences.

compared to US evidence in De Loecker et al. (2020), relatively small. Both estimates show that markups are stable in the German manufacturing sector. Between 2003 and 2014 (years covered in Mertens (2020) and the CompNet data). The markups from the more sophisticated production function estimation and the markups based on the simple CompNet specification both increased by respectively 1.2 and 1.8 percentage points.

Both estimates thus conclude that although market concentration was severely rising over that period, firms' markups stay rather constant.[34] The high similarity in movements between both markups reassure us in the quality of the CompNet data.

Figure K.1 – Product markups in the German manufacturing sector. The blue solid line displays aggregate markups based on a complex translog production function routine controlling for firm-specific output and input price variation and correcting for the simultaneity bias resulting from firms' flexible input decisions. Estimates are taken from Mertens (2020). The red dashed line reports markup estimates from the CompNet data based on a translog production function estimated by OLS. Both markup series are cost-weighted aggregates of firm-level markups. German manufacturing sector firm-level data and CompNet data.

[34] Mertens (2020) shows that the low markup levels are explained by large labor market power of firms in the German manufacturing sector. He further shows that estimates in De Loecker et al. (2020) do not only measure product markups but are also biased upwards by any firm existing labor market power. In the German manufacturing sector, firms' labor market power is much higher than their product market power (i.e. firms generate large rents on labor markets that make them profitable despite low markups) (Mertens (2020)).

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