



EUROPEAN CENTRAL BANK
EUROSYSTEM

Working Paper Series

Maria Chiara Cavalleri, Alice Eliet,
Peter McAdam, Filippos Petroulakis,
Ana Soares, Isabel Vansteenkiste

Concentration, market power and
dynamism in the euro area

Discussion Papers

No 2253 / March 2019

Disclaimer: This paper should not be reported as representing the views of the European Central Bank (ECB). The views expressed are those of the authors and do not necessarily reflect those of the ECB.

2 Market Power: Some Basic Definitions

To understand the evolution of market power in euro area firms we focus in our analysis on three dimensions: market concentration, markups and economic dynamics. To obtain a comprehensive picture, we rely on micro firm level as well as macro sectoral data. Limitations to the data quality and availability (in particular for the micro data) imply that we focus our analysis on the four largest euro area countries, namely Germany (DE), France (FR), Italy (IT) and Spain (ES). This nevertheless should allow us to obtain a rather comprehensive picture, since these four countries combined represent almost 80% of euro area GDP. A detailed description of the data sources and transformations to the data are explained in [Appendix A](#).

¹⁰Note, differences in the levels across countries may be driven by data coverage, so they should be interpreted cautiously. Analysis based on trends is more robust.

2.1 Measuring market concentration

Market concentration measures the extent to which market shares are captured by a reduced set of firms. As noted above it is often taken as a proxy for competitive intensity. There exists a number of approaches to measure market concentration. The simplest is to compute the concentration ratio, (CR_q), which express the market share (MS) of the q^{th} largest firms in a market:

$$CR_{q,t}^s = \sum_{i=1}^q MS_{i,t}^s \quad (1)$$

This metric is bounded in the unit interval, where q is typically set to values such as 4, 10 and/or 50. Here we use $q = 4$, and thus the CR_4 denotes the combined market shares of the four largest firms. In turn, $MS_{i,t}^s$ is the market share of firm i , in year t and industry s :

$$MS_{i,t}^s = \frac{sales_{i,t}^s}{\sum_{i=1}^{N_t^s} sales_{i,t}^s} \quad (2)$$

where N_t^s is the number of firms in industry/sector s and year t .

Indicator (1) considers exclusively the relevance of the top q firms and disregards the distribution of market shares of a given industry. The concentration ratio captures the ability to collude (as the number of firms in an industry falls, collusion is expected to increase). Note, to meaningfully interpret the CR_q measure, one first needs to determine the *relevant market*, i.e. which firms and products to include when calculating the market shares. We shall discuss these issues further in Section 4.

Moreover, concentration ratios such as a CR_4 inevitably do not distinguish between markets in which there are only five firms and those where there is a long tail of firms with smaller market shares. The Herfindahl-Hirschman index (HHI) solves this problem by calculating the square of the market share of each firm in the market, and summing the resulting numbers:

$$HHI_t^s = \sum_{i \in s}^{N_t^s} MS_{i,t}^{s^2} \quad (3)$$

The HHI index ranges from close to 0 under perfect competition to 10,000 in monopoly (i.e., 100% market share). When there are n equal-sized firms HHI equals $1/n$. The empirical literature defines $HHI < 1000$ as the threshold for low levels of concentration and $HHI > 1800$ as highly concentrated markets. One advantage of the HHI is that it does not only take into account the equality of market shares across firms but also the number of firms in the industry. Accordingly, we consider both CR_4 and HHI measures in our analysis (albeit concentrating on the former in the main body of our text).

2.2 Markup definition

The market power of a firm relates to its ability to sustain prices above marginal costs. The markup ratio ($\mu_{i,t}$) measures the gap between the price and the marginal cost and it is defined as follows:

$$\mu_{i,t} \equiv \frac{P_{i,t}}{MC_{i,t}} \quad (4)$$

where $P_{i,t}$ and $MC_{i,t}$ are the price and marginal cost, respectively, for a given firm i in year t . Under perfect competition, it equals one as prices match marginal costs. The degree of market power is increasing in the gap between prices and marginal costs. The markup ratio is closely related to the Lerner index also known as the price-cost margin ($PCM_{i,t}$). It is defined as follows: $PCM_{i,t} = 1 - \frac{1}{\mu_{i,t}}$, where the $PCM_{i,t} \equiv \frac{P_{i,t} - MC_{i,t}}{P_{i,t}}$.

The markup at industry level s corresponds to a weighted mean of firm-level markups according to the corresponding market shares as follows:

$$\mu_t^s = \sum_{i=1}^{N_t^s} MS_{i,t}^s \times \mu_{i,t}^s \quad (5)$$

where, as before, $MS_{i,t}^s$ is the market share of firm i , in year t and industry s . We shall discuss aggregation issues in more detail in Section 4.

The main problem when computing markups is that prices are generally not available and marginal costs are unobservable. To overcome these shortcomings, the empirical literature has developed a variety of approaches. In line with these, in our analysis we assume constant returns-to-scale, that capital is a fixed cost and, consequently, that average costs are a suitable proxy for marginal costs. What constitutes “marginal costs” for the firm is by no means settled, and can have an impact on the level and dynamics of the markup measures (e.g., Traina 2018). Moreover, data availability and comparability across countries and sectors can make precise calculations difficult.¹¹

2.3 Economic Dynamism

Market economies are characterised by a continuous reallocation of resources across firms and sectors. Myriads of jobs are destroyed and created every year, new firms are born, old ones die, and continuing ones grow or downsize, with gross flows of workers, jobs, and firms dwarfing net flows.

According to canonical models of firm dynamics (Hopenhayn 1992), such reallocation of resources is critical for productivity growth. Resources (capital and labour) are expected to flow from less to more productive firms. This raises aggregate productivity directly, as resources move to more productive uses, but also indirectly, as the in-

¹¹ Note, given some data constraints on the macro side, and the short time span of the micro data side, we chose not to implement the recent De Loecker & Warzynski (2012) markup methodology.

creased availability of resources allows these firms to expand further. Reallocation also enhances the productivity contribution from the entry of new firms and the exit of weak incumbents. The contribution of young firms is especially important: young firms enter markets in search of new opportunities, introduce new products and innovations, and are an important source of employment growth (Bartelsman et al. 2000).

A host of inefficiencies and rigidities can hinder entry and reallocation. High barriers to entry that protect the rents of incumbents, an unfriendly business environment in the form of large administrative costs, insufficient credit and an absence of specialised finance for new ventures. Rigidities in the exit margin are also important. Weak firms may inefficiently stay in the market through insolvency frameworks that prevent restructuring or resolution, weak banks that want to avoid recognising losses, or political pressure. This congests healthy incumbent firms, and can impair productivity growth (Adalet McGowan et al. 2018, Andrews & Petroulakis 2017).

This economic dynamism is typically captured by the measures of so-called firm ‘churn’:

$$Birth\ Rate = \frac{Entering\ Firms}{Active\ Firms} \times 100 \quad (6)$$

$$Death\ Rate = \frac{Exiting\ Firms}{Active\ Firms} \times 100 \quad (7)$$

$$Churn = Birth\ Rate + Death\ Rate \quad (8)$$

In the De Loecker and Eeckhout framework, under certain conditions, rising markups can explain the concurrent decline in the rate of labour reallocation in the US over the same time. Rising concentration and depressed levels of economic dynamism are intuitively related. Barriers to entry mechanically translate into higher market power for incumbents. Conversely, firms with high market power may use it to deter entry, through the threat of a price war or privileged access to partner firms, or lobby for the establishment of occupational licenses. Power in product markets may directly imply power in labour markets (where firms can pay wages below marginal product), which may be further entrenched by the enforcement of non-competing clauses or no-poaching agreements (Ashenfelter & Krueger 2017).

As regards job reallocation, relying on the job-finding and employment-separation rates (the unemployment-to-employment and employment-to-unemployment transition rates), we follow the Shimer (2012a) to estimate these from aggregate data. Let the unemployment rate u_t evolve as

$$\frac{du_t}{dt} = s_t(1 - u_t) - f_t u_t, \quad (9)$$

where s_t is the monthly rate of inflow into unemployment (or the separation rate) and

f_t is the monthly outflow rate from unemployment (or the finding rate). Letting the stock of unemployed be given by U_t , the stock of unemployed for less than 1 month by $U_t^{<1}$, and the probability of exiting from unemployment within 1 month by $F_t^{<1}$, then the change in the stock of unemployed within 1 month is given by:

$$u_{t+1} - u_t = u_{t+1}^{<1} - u_t F_t^{<1}. \quad (10)$$

Similarly, the separation rate can be obtained by solving (9) forward to obtain (using the definition $f_t^{<1} = -\ln(1 - F_t)$)

$$U_{t+1} = \frac{[1 - e^{-f_{t+1} + s_{t+1}}] s_{t+1}}{f_{t+1} + s_{t+1}} (U_t + E_t) + e^{-f_{t+1} + s_{t+1}} U_t, \quad (11)$$

where E_t is the stock of the employed. For the euro area, since monthly inflow and outflow rates are too low to be captured by survey data, we use the adaptation of this method by Elsby, Hobijn & Şahin (2013), and optimally combine inflow and outflow rates for 1, 3, 6, and 12 months.

The finding rate is the hazard rate associated with the probability that an unemployed individual will find a job, and the separation rate is similarly related to the probability that an employed individual will lose her job. These probabilities are not identical to job creation and destruction. A worker may lose her job (increase in the separation rate) without an increase in job destruction if the job is filled immediately. If the job is filled with a worker coming out of unemployment the job finding rate will increase, but not if the new worker switches immediately from another job. There are disagreements as to whether the finding and exit rates or the destruction and creation rates are more important over the business cycle, but it seems rather innocuous to consider the trend behaviour of job-finding and job-exit rates as sufficient statistics for the trend of job reallocation. While it is well-known that the US labour market is much more dynamic than any European labour market, with exit and entry rates in the US dwarfing those in Europe, here we are concerned with the evolution of dynamism over the past two decades rather than its actual level.

3 Relationship to the Literature

Understanding the extent of firm market power is of relevance in many branches of economics. Industrial organization economists and competition authorities have a long history of studying firm market power.

Traditionally however it attracted far less attention among macroeconomists, who only started studying markup behaviour in the mid-1980s and even then, they were more interested in analyzing the cyclical rather than trend behavior of markups. This

can in part be explained by the fact that macroeconomic models are generally founded on Kaldor's stylized facts, such as a constant labour share, constant profits and a constant capital-to-output ratio. The models thus implicitly assume no trend changes in firm market power. Only recently, the analysis of trend developments in market power has entered the field of macroeconomics in response to a number of studies which found that there may be a potential sustained rise in market power.

The topic was most prominently brought to the fore in recent years by De Loecker & Eeckhout (2017). They suggested that the average markup for US firms has risen sharply over the past three decades. More specifically, they find that the increase occurred across industries but was mostly concentrated within high markup firms (i.e. those firms that had a high markup at the beginning of the sample witnessed the biggest rise in markups).¹² De Loecker & Eeckhout (2017) further link these developments to a number of secular macro trends, such as the decrease in labour and capital share, the decline in low skilled wages, the decline in labour flows, labour force participation and migration rates and the slowdown in aggregate output. In addition, Eggertsson, Robbins & Wold (2018) also find that a rise in pure profits or market power could be driving some of the recently observed macroeconomic trends, including the decline in both the capital and labour share and a rise in inequality (Edmond et al. 2018). A further nuance to this debate concerns the rise of common ownership, whereby, through the rise of passive asset management, the largest asset management institutions in the United States (such as BlackRock, Vanguard, State Street) collectively own large shares in natural competitors across a wide range of industries. Taking common ownership into account can vastly increase measures of concentration (Azar et al. 2018) and have important consequences. When shareholders own shares in different competitors, they may be more reluctant to engage in competitive pricing, innovation, investment or any other activity that may reduce the profits of commonly owned competitors. Externalities and spillovers may be sufficiently complex that common ownership raises R&D (Lopez & Vives 2019) and common ownership across many sectors may raise aggregate output (Azar & Vives 2018). Overall, however, under reasonable calibrations, common ownership has an overall negative effect on the economy and has been shown to be able to explain the secular stagnation hypothesis (low output growth, declining labour share) (Azar & Vives 2019).

There have been also a number of other studies, using different approaches and methodologies, that point towards a rise in market power of US firms. For instance, Hall (2018) and Nekarda & Ramey (2013) also find, in this case using macro data, support for the conclusion that the markup has risen for US firms in recent decades. Moreover, tak-

¹² As De Loecker & Eeckhout (2017) state: "The decomposition shows that since the 1980s, the change in markup is mainly driven by the change within industry. There is some change in the composition between industries, but that is relatively minor compared to the within industry change. The change due to reallocation, the joint effect, is mostly small." (p13).

ing a different angle, a number of studies also show that concentration ratios have been rising (see overview [Table 1](#)) and Barkai (2016) found that the decrease in labour share of value added is not due to an increase in the capital share but rather by an increase in the profit share, which went from 2% of GDP in 1984 to 16% in 2014.

However, whereas there is by now broad based agreement that firm markups and concentration ratios have increased in the United States, there is far less agreement on the magnitude. Indeed, markup estimates range widely across studies, with Traina (2018) finding that the increase in markups between 1980-2016 is within historical ranges, while De Loecker & Eeckhout (2017) at the other extreme find that markups have risen from 18% in 1980 to 67% in 2014.

There is even less agreement on the drivers of this potential increase in market power. One less benign explanation is that changes to US merger policies have made it easier for firms to build, protect and extend positions of market power through anticompetitive mergers and that this has had a bigger impact on increasing market power than it did in delivering efficiencies (see for instance Peltzman (2014) and Blonigen & Pierce (2016)). Another possibility is that firms have been successful in lobbying and rent-seeking for regulatory protection. For instance, Bessen (2017) finds that regulation and campaign spending are responsible for an increase in markup of 1-2 percent. Zingales (2017) stressed that while lobbying and rent seeking have always existed, this has worsened recently through a vicious circle of market concentration and political power. More concretely, as firms have recently gained market power, their capacity to exert political pressure to protect and increase their market power has also risen.

However, other authors have found that the documented rise in market power may reflect much more (potentially) ‘positive’ economic developments as firms earned it thanks to repeated successes in innovating and distinguishing themselves from their rivals and/or cutting costs and improving their productivity. Autor et al. (2017a) describe this as the ‘superstar’ firm hypothesis. Such a development may result in an increase in markups, profit and concentration that is also accompanied by lower costs, higher product varieties and higher productivity. Digitalization and globalization may have recently facilitated such developments. As a potential confirmation of this view, Calligaris et al. (2018b) find that markups are higher in digitally intensive sectors. Along similar lines, Crouzet & Eberly (2018) suggest that intangible investment has been an important driver behind the recent rise in markups and firm concentration in some US sectors.

While the debate and analysis in the United States is already at a rather advanced stage, our understanding of these trends at the euro area and global level is much more limited. In part, this can be explained by data limitations and cross-country comparability issues. Nevertheless, there is also here a nascent literature developing. An overview of these studies is presented in [Table 2](#). As the table shows, no consistent message arises so far on the evolution of market power at the euro area or global level. While a number

of studies indicate that at European (and even at global) level we are witnessing similar trend developments as in the US, other studies do not observe such developments (and in some cases, they even document a rise in competition). In this regard, Gutierrez & Philippon (2018) find that while until the 1990s, US markets were more competitive than the European markets, the situation has reversed, with European markets having lower concentration, lower excess profits and lower regulatory barriers to entry. The authors attribute this change, inter alia, to a delegation of anti-trust enforcement to the euro area level.

4 Aggregation and “Relevant Markets”

In Section 2, we explained our three main indicators of market power. However, making sense of such indicators requires us to integrate additional issues of geographical coverage and market size. Simply calculating, for instance, an aggregated markup without controlling for the size of the relevant firms or economic size of the interacting markups gives a distorted view. Accordingly, in this section we define some logical and algebraic boundaries to our metrics.

Consider a concrete example – say the Tobacco industry (which sells a fairly homogeneous internationally-trade product), in one country, say France. If there is only one French tobacco Manufacturer, we might conclude that this firm has a monopoly, warranting an examination by the relevant competition authorities. However citizens in France may also use British or German tobacco products. Indeed, the French Tobacco Manufacturer may – when all such sellers are considered – enjoy a very limited market share. These considerations naturally prompt some discussion of how and where we define the market and how we aggregate sectors and countries.

4.1 Relevant Markets

A comprehensive definition of the relevant market takes into account the degree of product substitution, transportation costs and the geographic location of producers and consumers. Given the difficulty in defining relevant markets, we follow much of the empirical literature which relies on an economic activity classification such as the NACE. In this context, we use 2 digit level as a market segmentation criterion. The underlying assumption is that firms sell one good and serve one industry defined at 2 digit in NACE Rev.2. Naturally, the presence of multi-product firms is likely to be a source of bias, especially if a firm sells products that are not close substitutes.

Over the years, the European Union has taken several steps to increase economic integration. Notwithstanding, there is evidence that there are still barriers to entry and exit related for instance to institutional frameworks that have prevented a complete in-

tegration in particular in industries less exposed to international trade.

In this context, we consider two operational concepts:

1. **Partial Integration: Country Aggregation (CA)**

In this case, the assumption is that each firm competes with firms that sell goods in the same industry and in the same country. Hence market shares are computed in a given industry and year for a given country in the Single Market. Thus, the aggregation of industries yields a country result for DE, FR, ES and IT. To obtain a country aggregate (as opposed to a Single-Market aggregate discussed below), we need to further aggregate countries into a euro area dimension. It corresponds to a country aggregate (CA) computed as a weighted mean of country level results as follows:

$$I_t^{CA} = \sum_s W_t^c \times I_t^{WM,c} \quad (12)$$

where $I_t^{WM,c}$ is the indicator of interest (μ_t^{WM} , HHI_t^{WM} and $CR_{4,t}^{WM}$) computed at country level in year t as a weighted mean across industries. W_t^c are country weights based on output using the EU-KLEMS dataset.

Since this first scenario may be a restrictive hypothesis in some industries, we consider an alternative scenario, which we call the Single Market.

2. **'Full' Integration: Single Market (SM)**

Each firm in this scenario competes with European counterparts in the same industry. At this level, one important challenge is that this set of firms operating in the Single Market is not entirely observed. There are important constraints on data collection which translate into lack of representativeness and comparability on several variables. Here we consider DE, ES, FR and IT as the relevant set of countries.

Recall the definition of market share of firm i , in year t and sector s : $MS_{i,t}^s = \frac{sales_{i,t}^s}{\sum_{i=1}^{N_t^s} sales_{i,t}^s}$, where, as before, N_t^s is the number of firms in industry s and year t . Under the first scenario, market shares are country specific and N_t^s includes exclusively the set of resident firms. On the Single Market case (SM), N_t^s includes all European firms (DE, IT, FR and ES) in industry s and year t . Naturally, and by definition, market shares are lower under the SM scenario compared to the aggregation of country results.¹³

¹³ Note that imports in a given industry (beyond the European firms) are disregarded and that sales consider not only domestic revenues but also exports.

4.2 Aggregation

Within these two scenarios – the Single Market (case) and the country specific results – We consider several aggregation strategies as follows:

4.2.1 CR_q and HHI

– Weighted mean

To obtain figures for the aggregate economy, we consider a weighted mean (WM) as follows:

$$I_t^{WM} = \sum_s W_t^s \times I_t^s \quad (13)$$

where I_t^s is HHI_t^s or $CR_{4,t}^s$ which are measures computed at industry level s and year t . W_t^s are industry weights based on output using EU-KLEMS. We rely on this last source to ensure representativeness.

– Un-weighted mean

To ensure that the dynamics is not driven exclusively by changes in weights over time, we consider also the un-weighted mean ($unWM$).

$$I_t^{unWM} = \sum_s I_t^s \quad (14)$$

– Median

In addition, we also consider the median across industries for a given year for the CR_4 and the HHI as follows:

$$I_t^{Median} = Median(I_t^s) \quad (15)$$

4.2.2 Markup

– Weighted mean

To obtain figures for the aggregate economy, we consider a weighted mean as follows:

$$\mu_t^{WM} = \sum_s W_t^s \times \mu_t^s \quad (16)$$

where μ_t^s is the markup computed at industry level s and year t . W_t^s are industry weights based on output using EU-KLEMS.

– Moments.

Median and Upper Decile from the firm-level distribution (respectively, the 50_{th} and 90_{th} percentile). In order to discuss the role of the firms in the top of the

distribution, we consider two moments in the firm-level distribution for a given industry and aggregate these moments using industry weights.

$$\mu_t^{90} = \sum_s W_t^s \times \mu_t^{90,s} \quad (17)$$

$$\mu_t^{50} = \sum_s W_t^s \times \mu_t^{50,s} \quad (18)$$

- The mark ups of the largest firms (i.e., specifically those identified in the CR_4 index): The top of the markup distribution is, according to recent evidence, driving aggregate markups in the US: sectoral shares remained broadly stable and all variation seems to be within sector particularly by the top of the distribution. While the top of the markup distribution does not necessarily comprise the same set of firms, these are also not necessarily large firms.

To discuss this issue we compare the following two indicators:

Indicator 1: The Mark up of the 4 largest firms

$$\mu_t^{s,L} = \sum_{i=1}^4 \mu_t^{s,SM} / 4 \quad (19)$$

where i include the four largest firms in a given sector s (included CR_4). As above, sectors are aggregated into a SM result as follows: $\mu_t^{SM,L} = \sum_s \mu_t^{s,L} \times W_t^{s,SM}$, where $W_t^{s,SM}$ is the weight of a given sector s year t based on EU-KLEMS data (based on the data for the 4 countries) and:

Indicator 2: The Markup of the Total Economy

$$\mu_t^{WM,SM} = \sum_s W_t^s \times \mu_t^{s,SM} \quad (20)$$

where μ_t^s is the markup computed at industry level s and year t (computed as a weighted mean between market shares in SM and firm-level markups). W_t^s are industry weights based on output using EU-KLEMS (using data for the 4 countries).

5 Data

We now briefly overview the data sources and treatment, on the macro and micro side. [Appendix A](#) describes the data in greater detail as well as various trade offs among the different data sets and the treatment and ‘cleaning’ that we applied.

5.1 Macro Data

We use macro data from the EU-KLEMS database (September 2017 Statistical Release), which provides information for DE, FR, IT, ES, a number of other European countries and the United States. For some variables, countries, and sectors, the series are available on a long time span, as early as 1970; however, a valid common sample across the selected countries only covers the period 1995-2015.

We will hence focus on this specific period for the cross-country analyses. We examine six macro-sectors defined at the 1-digit level and follow the NACE Rev.2 classification. The macro-sectors considered are: Manufacturing (NACE 2 category C), Water, Electricity and Gas (NACE 2 category D-E), Construction (NACE 2 category F), Wholesale and Retail Trade (NACE 2 category G), Transportation (NACE 2 category H), Non-financial Services (NACE 2 categories I, L, and M-N).

5.2 Firm-Level Micro Data

We rely on two sources of data for the analysis at the firm-level: the Orbis database from Bureau Van Dijk; and iBACH data. iBACH is our main source but it only includes information for France (FR) and Italy (IT). Other countries, Germany (DE) and Spain (ES) are collected through Orbis.

Regarding Orbis-Europe, we use a customized version requested by the ECB with no attrition bias which is imposed when collecting data through online access. However, some features of the firm such as location, sectoral classification, legal form, year of incorporation (entry), status of the company (active/liquidation/merger-acquisition) and quoted/unquoted indicator are time invariant and relate to the last year. There is information on Orbis at this level (merging vintage data) however this is not currently available at the ECB. There is a 2 year reporting lag, on average, from Orbis and 2015 is the last available year.

The iBACH firm-level dataset is gathered through national central banks (NCBs) in the euro area in joint work with ECB Directorate General Statistics. Substantial effort is placed on having variables that are comparable across countries. The source of this data is mainly administrative though not entirely homogeneous across countries. It is an alternative to Orbis since it overcomes their main problems but the only countries available are FR, IT, PT (Portugal), BL (Belgium) and ES (and some other, mainly small, countries such as Slovakia). The financial sector is not part of iBACH dataset and for this reason it is excluded from the analysis.

6 Evidence of the evolution of market power of euro area firms

6.1 Concentration Measures

Figure 1 shows the evolution of the CR_4 measure over our micro sample, both for the Total Economy and for the Manufacturing sector. The main reason to isolate Manufacturing is that measurement error is likely to be lower and at the same time integration across tradable goods in the euro area is expected to be higher. Moreover, in our later analysis we isolate margins (such as technological take up) that are only available at the Manufacturing level. Consistent with our earlier discussion, we observe that by definition the Country Aggregate concentration ratio will always strictly exceed that of the Single Market indicator (although this need not hold for the markup measure).

We see that the top 4 firms in the Total Economy account for between 10% and 22% of total market shares (depending on whether you use the Single Market or country-aggregate measure). Manufacturing has relatively higher concentration levels (around 14 – 30%). This is hardly surprising since Manufacturing, when comparing to the Total Economy, typically involves higher fixed costs and often more emphasis on scale economies which tends to provide a bound on the number of entrants. Interestingly, as we shall see below, Manufacturing tends to have lower markups than the Total Economy for equivalent reasons (e.g., traded nature of goods produced).

Notwithstanding, we find that in both polar cases (i.e., Country Aggregate, and Single Market) the *dynamics* of concentration are essentially flat over the last 10 years both for the Total Economy and the Manufacturing sector. There was though – after the volatility of the financial crisis – some minor general increases in the concentration ratios, presumably reflecting the exit of some producers and firm amalgamations. Naturally, this could be a rather short time frame to evaluate structural changes, although De Loecker & Eeckhout (2017) found much of the rise of market power for the US economy occurring over a not too dis-similar time frame (albeit for those authors, shift were considered in terms of markups).

Overall, thus, the results suggest that market concentration in the euro area has remained broadly flat since 2006, both at the Single Market and national (Country Aggregate) level. As such, these results confirm the conclusions in the existing literature (see Table 2). Looking at the countries separately (see Figures 2 and 3), we find that the Manufacturing sector is on average somewhat more concentrated and also that concentration is higher at the country level than at the single market aggregate level (in line with Gutierrez & Philippon 2018). Across countries meanwhile we find that Italy appears to be least concentrated, while Germany the most. Over time, concentration has been broadly flat in most countries, albeit declining somewhat in Germany and increasing

slightly in Spain.

6.2 Markup Measures

We now turn our attention to another indicator of market power, namely firms' markup. In this respect, unlike the concentration measures for which we can only rely on micro data, we can exploit both long-dated macro data *and* micro data. This is especially useful since much of the debate over the markup has tended to focus on whether recent decades have seen a change in its trend.

Figure 4 shows that average markup for the economy as a whole – based on macro sectoral data – has remained broadly stable over the period 1978-2015 at a mean of around 13% (thus implying the prices are on average 13% above marginal costs). There has been a mild reduction (or perhaps stabilization) of the markup trend from the late 1990s/early 2000s driven potentially by the gains in intra-EU competition which might be expected from the start of the Single Market in Goods and Services in 1993 and the start of the monetary union in 1999. This (downward) trend is also apparent to a greater degree in Manufacturing, with the average markup trending noticeably particularly from the mid to late 1990s with an overall mean of around 5%. This is consistent with our prior that margins in Manufacturing are smaller given the tradeable and substitutable nature of its products and the high costs (including presumably high variable costs) that may be involved in production. Figure 5, moreover, shows that this trend is quite uniform across the constituent countries.

These results contrast with US developments. As shown in the figure (and widely documented in the literature, recall Section 3), average markups have been on an upward trend in the US.¹⁴ This is observable in both the Manufacturing sector and the Total Economy, but has been most pronounced in the former. Concretely, using sectoral EU-KLEMS data, the average markup in the US is estimated to have increased by 9% and 12% in the Total Economy and Manufacturing, respectively.

To pursue these issues more fully, we can shift our attention to our micro data sources. Figure 6 shows the markup in our four euro area countries from 2006 (for both Total Economy and Manufacturing) given the variety of definitions described in Section 4. It is worth noting at the outset that the markup we find on the micro data (from 2006 onwards) is in the ballpark of the macro markup of that period (around 10% for the Total economy, and under 10% for Manufacturing) and follows a similar dynamic.¹⁵

Firm level data also allows to consider the full distribution of markups. For the US,

¹⁴ Note, that we do not replicate the dramatic evolution of De Loecker & Eeckhout (2017) for the US markups – given that we do not use their (CompuStat) database. We do however replicate qualitatively their path.

¹⁵ Although of course given what is known in micro to macro aggregation there is no necessity that the two would necessarily yield a similar picture.

firm level data have shown that the rise in markups has been most pronounced at the top end of the distribution (see for instance De Loecker & Eeckhout 2017 and Díez et al. 2018). The upper (orange) dashed lines (in both panels) reveal there are firms among our sample who do enjoy relatively high markups (around 20 – 30%) and (at least for the Total Economy) exhibit a marginally rising path. The question remains of who these firms are; are they economically meaningful in size? This is important, since De Loecker & Eeckhout (2017) argued that the rise in the aggregate markup is driven by the increasing sectoral share of firms with a pre-existing ‘high’ markup. In other words, the top of the markup distribution is driving the aggregate markup. Since sectoral shares remained broadly stable, all variation seems to be within sector, particularly at the top of the distribution.¹⁶

However, as Figure 7 reveals, this is not so for the euro area. Here we take the previous mean for the markup (the previous blue line in Figure 6) and then restrict our attention to the markups associated to the CR_4 set of firms (the brown line). As can be seen there is no major difference between them (and no statistical significance).

6.3 Is there a relationship between markups and concentration?

So far we have looked at markups and concentration in isolation. Interestingly, the link between them – both empirically and in theory – is by no means clear cut, Tirole (1988). There may be firms with ‘high’ markups but which operate in a sector with many competitors (e.g., both domestic and non domestic). Alternatively there may be firms with limited markups but who are dominant in their industry (as judged by their market shares). This begs the question of why there should be such differences. One explanation may rest of the afore-mentioned Shumpetarian framework and the potential contestability of markets. Another is firms’ technological characteristics. We examine these issues in later sections.

Figure 8 combines the evidence on concentration and markup evolution at the NACE rev. 2 level. It shows the evolution of markups in low (blue) versus highly (red) concentrated sectors (as reflected in their CR_4 rating).¹⁷ If outcomes are unchanged, then the dots (all of them) will be clustered on the diagonal. That they mostly are, confirms that markups (at least by sector) are reasonably stable (although remember that this is a short sample, so we might expect such stability).

Moreover, as regards the markup changes in low versus high concentrated sectors, no clear pattern emerges, i.e. markup changes were not concentrated in either the low or high concentrated sectors. That said, there is a clustering of dots around the low markup low concentration region. Furthermore, there are some interesting and illustrative

¹⁶ For an overview of sectoral shares in the euro area and the US see Figure B.3 in the appendix.

¹⁷ By high and low we mean above and below sample median.

tive cases to examine. For instance, *Air Transport* is highly concentrated (as you would expect of an industry with huge fixed costs and operating in a high regulatory environment) but its weighted markups are fairly low. Whereas *Telecom* (also an industry with high fixed costs and relatively high barriers to entry) is also highly concentrated but enjoys a quite substantial markup. Although note that markup in Telecoms has been going down – reflecting deregulation in the industry and increasing competition from other media platforms. At the other end we have *Real Estate and Rental* which are not especially concentrated but they do enjoy an above-average markup. This may reflect that firms in this sector compete in non price terms, or, being mostly local services, are not exposed to international competition. Figure 9 repeats the earlier figure but wherein the size of the bubbles represent the respective share of the sectoral turnover over total sales.

6.4 The Case of ‘Superstar’ firms

Autor et al. (2017a) and Autor et al. (2017b) argue that some firms and industries are increasingly characterized by a winner-takes-all effect – i.e., attaining large market shares from higher productivity and more demanded product ranges but with a relatively small workforce (popular examples being Facebook and Google). They describe this phenomenon as the superstar firm hypothesis.

The emergence of such firms could be related to: i) the diffusion of new competitive platforms (e.g., easier price/quality comparisons on the Internet) ii) the proliferation of information-intensive goods that have high fixed and low marginal costs (e.g., software platforms, cloud computing, and online services), iii) rising international integration of product markets.¹⁸ Such developments may result in an increase in markups, profit and concentration that is also accompanied by lower costs, higher product varieties and productivity. This dynamic, moreover, may be self reinforcing.

Figure 10, taken from Autor et al. (2017b), plots the average sales- and employment-based CR_4 and CR_{20} measures of concentration across four-digit industries for each of the six major US sectors. We see an upward trend over time – according to all measures, industries have become more concentrated on average, stronger when measuring concentration is measured in sales rather than employment. The precise welfare implications of such ‘superstar firms’ is far from clear, though. On one hand, their productivity can potentially raise general productivity and release resources for other sectors (and thus for the development on new industries and new products). On the other hand, they may create a polarized labour market (into high and low skill, and ‘good’ and ‘bad’

¹⁸ As a potential confirmation of this view, Calligaris et al. (2018b) find that markups are higher in digitally intensive sectors. Along similar lines, Crouzet & Eberly (2018) suggest that intangible investment has been an important driver behind the recent rise in markups and firm concentration in some US sectors.

jobs) with resulting (likely negative) effects on the overall labour income share.¹⁹

For the euro area, however, we find little evidence that such firms are emerging over our sample period, see Figure 11 and Figure 12. Here we tag firms in their CR_4 forms, then compute the share of employment in the sector and aggregate up using country weights based on employment. We do not observe that the large firms are decoupling their sales and employment trends, except perhaps for ‘Other Services’.²⁰ At the same time, our micro data frame may be rather short to look at structural dynamics such as the Superstar phenomenon.

7 Measuring economic dynamism

In this section, we examine the evolution of dynamism in the euro area and the US, focusing on job reallocation. The US comparison is particularly revealing since (i) we witness marked differences (in both trend and level) relative to the euro area and (ii) technology uptake seems to be a key underlying reason (which is helpful also to discuss in the European context). As job reallocation data require administrative datasets on the job flows across firms, which are not readily available across the euro area, we consider the job finding and separation rates, the probability of an unemployed worker to find a job and the probability of an employed worker to become unemployed, respectively. It should be noted that the rich US literature on dynamism also considers measures of economic dynamism, typically firm birth and death rates. The complication here is that data on economic dynamism for European member states are plagued by with severe asymmetries in coverage, different conventions on business types across countries, and different definitions of firm dynamics than the US. See Appendix C for details.

Falling market dynamism has been well-established for the US. De Loecker and Eeckhout document an increase in the volume and value of mergers and acquisitions. They also document an increase in the size of listed firms and a reduction in their number, starting in 2000, and interpret these two facts as an increase in the consolidation of corporate ownership, and hence market power. They also find that markups are positively related to firm size within sectors, as predicted by standard models of competition.

Decker et al. (2016) show that until the early 2000s, the growth distribution of young firms was highly skewed, with the median young firm either disappearing or stalling, but with the right tail dynamic enough to carry the mean. Since then, this skewness has drastically diminished. In addition, Decker et al. (2018) show that lower dynamism is

¹⁹ This is a controversial area and beset by data issues. For instance, it is not clear that the literature is capturing hours worked (e.g., part-time workers) or trends in international out-sourcing of jobs and tasks.

²⁰ ‘Other services’ includes sectors 55-82 except Financial Activities: Accommodation and Food Service Activities, Information and Communication, Real Estate Activities, Professional, Scientific and Technical Activities and Administrative and Support Service Activities.

the result of lower responsiveness of firms to productivity shocks compared to previous decades, indicating a rise in frictions and distortions preventing firms from realising their potential.

Figure 13 shows the evolution of the churn and birth rates for US establishments since 1980. The long-run secular decline in dynamism is evident, despite occasional bursts of activity, which are to some extent the result of growth in the high-tech sector, and the trend substantially slows down in the aftermath of the crisis. For Europe, we refer to Figure 14, which comes from the harmonized cross-country analysis of Criscuolo et al. (2014). While there is a downward trend in start-up rates across several countries, the pattern is not ubiquitous. For instance, in the UK, the Netherlands, Portugal, Belgium, Sweden and Finland, start-up rates were either steady or trending up before the crisis. The absence of data during the recovery is a limitation to a comprehensive analysis of this issue.²¹

The estimated finding and exit rates are shown in Figure 15 for the US over 2000q1-2017q4. There is an obvious cyclicalality in the job-finding rate; it was very high in 2000, at the height of the dot-com bubble, and plunged to a little over 20% in 2010, with unemployment at almost 10%. While it has rebounded substantially, it is still below its pre-crisis peak, despite unemployment being lower at the end of the sample than its pre-crisis trough. Even the pre-crisis peak was much lower than its level in 2000. Indeed, unemployment in 2017q4 was 4.1% and the monthly finding rate 49%; in 1999q4, with unemployment also at 4.1%, the monthly finding rate was 75%. This secular decline in labour market dynamism becomes starker once we consider the trend behaviour of the job-separation rate. With the exception of a brief cyclical spike at the onset of the crisis, it has been on a clear secular decline since the beginning of the 2000-2017 period examined here. In fact, the decline started around 1980, which coincides well with the initial phase of the decline in dynamism.

Figure 17 repeats this exercise for the euro area.²² Though the job-finding rate is an order of magnitude lower than the US, there does not seem to have been a particular change in the trend of labour market dynamics. The job-finding rate declined sharply in 2009, and then again in 2011 and 2012, in line with the cycle, but it has increased considerably with the recovery, to levels consistent with historical experience.²³ For the separation rate, a similar picture emerges; it fell before the crisis, then exhibited twin peaks coinciding with the two stages of an increase in the unemployment rate, to fall

²¹ Note that the declining dynamism observed for Spain has been documented for a more recent period by Benito-Moral & Queiros (2018).

²² There is too little movement at monthly frequencies in the euro area, so we employ the method of Elsby, Hobijn & Şahin (2013) and estimate transition rates at different durations and weight them optimally to calculate average rates.

²³ The predicted value from a regression of the job-finding rate on unemployment is 7.25% for 2017q4, almost identical to actual value of 7.32%.

again with the current recovery. Indeed, the finding rate is well-captured by unemployment.²⁴

Overall, the evidence suggests that the well-documented reduction in economic dynamism in the US **does carry over** to the euro area, at least not with the same intensity, and certainly not in the labour market. By most metrics, the US economy remains more dynamic than the euro area economy, but the question here is in terms of trends, not levels. While the euro area remains less dynamic than the US, it is not clear that it is particularly less dynamic than it was over the early 2000s.

What could be behind the apparent divergence in dynamism between the euro area and the US after the mid-2000s? One possibility may be the differential role of the high tech sector in the two economies. In the US, a substantial part of the pre-crisis dynamism was driven by large reallocation in the high-tech sector, a particularly dynamic part of the economy, which has since become substantially more sclerotic, Decker et al. (2016). Once high tech is excluded, dynamism exhibits an even sharper decline and productivity gains since the early 1990s are primarily driven by consolidation in the retail sector, aided by ICT (Information and Communication Technology) innovations, and hence low dynamism. A simple way to measure the importance of the high-tech sector across countries is value-added share accruing to the ICT sector, defined in a harmonised way by the OECD.²⁵ In 2011, the US had 7.1% of its total value-added from the ICT sector, compared to 5.1% for Germany and France, 4.9% for Italy, and 4.6% for Spain. See also **Table 4** for some additional metrics on the IT divide between the euro area and the US.

8 The macroeconomic implications

So far our evidence suggests that while in the United States firm market power has increased in recent years, it has remained broadly unchanged in the euro area. What are the macroeconomic implications of these findings for the euro area? How do these essentially micro phenomena aggregate up to macroeconomic variables relevant to policy makers, such as investment and TFP? Put simply, even if market power developments are flat, nonetheless their effect still imparts an effect on the economy.

On the one hand, the conventional view holds that these developments are, from a welfare perspective, more favorable for the euro area. Having more competitive markets

²⁴In Figure 17a, we show the standardised residuals from a regression of the finding rate on unemployment rate for the two regions. The difference is stark; the residuals for the US show a clear downward trend, from initially positive to negative. For the EA, in contrast, the residual consistently fluctuates around zero, indicating that the evolution of the finding rate is well-explained by the cycle.

²⁵ This includes manufacturing of computer, electronic and optical products, telecommunications, computer programming and information service activities, software publishing. See <https://data.oecd.org/ict/ict-value-added.htm>

in the euro area would imply that firms invest and innovate more and therefore have lower costs and consumer prices (a point argued for instance by Gutierrez & Philippon 2018). However, on the other hand, it could also be argued that the euro area has missed out on the *superstar* firms, which enjoy some market power but also provide incentives to the firms to invest and to innovate.

The answer to this is *ex ante*, not straightforward, as noted in the Introduction. To shed light on this matter, we investigate the interaction between our concentration ratios, investment, total factor productivity (TFP) and markup developments at the sectoral level in the next sections.

8.1 The interaction between concentration and investment

We first focus on the relation between investment and market concentration over our data sample. We do so by estimating an equation that has the sectoral investment rate regressed on sectoral concentration ratios:

$$IY_{s,t} = \alpha_s + \alpha_t + \beta_1 CR_{4s,t-1} + \beta_2 CR_{4s,t-1}^2 + \varepsilon_{s,t} \quad (21)$$

where IY is the investment rate, CR_4 is the concentration ratio (as proxied at sectoral level by the market share of the four largest firms), t denotes the year and s denotes sector. We include in our analysis 23 sectors at NACE 2 level. The equation also controls for sector (α_i) and time (α_t) fixed effects. The inclusion of these fixed effects allow us to measure the impact of concentration, after controlling for broader macroeconomic developments and sector-specific aspects. To test for the presence of non-linearities, we include a quadratic term for sectoral concentration: this allows us to verify whether the inverted U-shaped relation, as highlighted by Aghion et al. (2005), is also present in our data sample.²⁶

The estimation results, reported in **Table 3**, indeed suggest a non-monotonic relation between investment and concentration. Higher concentration is initially associated with increasing investment, as indicated by the positive estimated coefficient β_1 . Beyond a certain threshold, however, increases in concentration become associated with lower investment, as indicated by the negative coefficient estimate for β_2 (it is negative for all industries).

Figure 18 also illustrates this relation. Essentially, what we see is a heavy cluster of low CR_4 -low I/Y firms. These are sectors which are either highly labour intensive

²⁶ Note that Aghion et al. (2005) conjecture that there is an inverted U-shaped relation between the degree of competition on the one hand and innovative activity on the other hand. Empirically, the authors document the relationship between the price cost margin on the one hand and the number of patents on the other hand. In our Discussion Paper instead, we proxy the degree of competition by the sectoral concentration ratios and innovative activity by the investment rate, with the latter being the best available proxy which is consistently and for a sufficient period of time available across the 4 big euro area countries.

(and thus may have low capital investment demands) or are firms which are fairly undynamic (for example, if they are not in contested markets). Similarly, we also have a cluster of firms which are not very concentrated but invest a lot. This is like a neck-and-neck story. An interesting intermediate cluster of low to medium concentration but high investment rates.²⁷ The overall fit is revealed by the red (non-linear) line.

8.2 The interaction between market power, markups and TFP growth

In a next step, we consider the relation between market concentration and TFP growth. Analyzing how market concentration relates to TFP growth among the largest euro area countries is relevant given the important role TFP plays in generating growth and raising living standards.

As is the case for investment, it is *ex ante* not obvious that there is a monotonic relationship between market concentration and TFP growth across sectors. On the one hand, some studies have highlighted the importance of *superstar* firms (see for instance Autor et al. 2017a). In this set-up, highly productive firms that benefit from increasing returns to scale (*superstar*), take an increasing market share given that “winner takes all” dynamics prevail. This will trigger a rise in market concentration but will also lift productivity and innovation. As such this development is consistent with reallocation to more efficient and innovative firms. However, high market concentration could also be driven by insufficient anti-trust enforcement and excessive barriers to entry. In this case, high market concentration could decrease economic dynamics and hamper productivity growth and innovation (see Gutierrez & Philippon 2017).

To analyze the relation between market concentration and TFP growth outcomes in the 4 big euro area countries, Figure 19 plots the kernel density of TFP growth over the period 2006 to 2015 for both the Total Economy and the Manufacturing sector. The results show that there is in fact a wide distribution of TFP growth outcomes. Splitting the results according to the distribution for the highest (i.e. top 25 percentile) and lowest (i.e. bottom 25 percentile) concentrated sectors, shows however that the width of the distribution differs importantly between high and low concentrated sectors. For low concentrated sectors, the distribution is more narrow than for high concentrated sector, implying that highly concentrated sectors are associated with more extreme outcomes, both “good” and “bad” (positive and negative).²⁸ For Manufacturing, again, we have

²⁷Note that we are using the investment ratio in this exercise, but TFP growth can also be used. In fact TFP growth distributions give somewhat sharper results. A caveat to the present analysis is that it uses investment in physical capital, while recent trends have seen a rising importance of intangible capital on firms’ production inputs, see Haskel & Westlake (2017).

²⁸ Given that there was a deep recession in the middle of our sample and that some of the most concentrated firms are in cyclically sensitive industries (such as Construction and Manufacturing), the generality of this concentration-as-spreading mechanism is unclear. For this reason, the crisis years were dropped from the kernel density plot. Deleting the crisis year attenuated this spread but did not remove it.

more disperse outcomes, but a notably fatter tail on the positive TFP growth side.

To understand the drivers of these more extreme outcomes in the highly concentrated sectors, we contrast these developments for low versus high technology intensive sectors. Low and high tech sectors are here defined according to the Eurostat definition for the Manufacturing sector.²⁹ This is a series combining various approaches to measuring high technology take up, including technological intensity (R&D expenditure/value added), trade in high-tech products, and the high-tech and biotechnology elements to patents.

Figure 20 shows the resultant kernel density plots for Manufacturing. For low tech industries, the distribution of TFP growth outcomes in low and highly concentrated sectors is nearly identical. Hence, the low tech industries appear to account neither for the very good nor the very bad TFP growth outcomes. The extreme results seem instead to be solely attributable to highly concentrated - high tech industries. These results would indicate that in the 4 big euro area countries both the good (superstar dynamics) and the bad drivers (barriers to entry) of concentration may be at work in these sectors. However, further and deeper analysis would be required to better understand and quantify the relative importance of the various drivers.

Interestingly, when looking at the markup dynamics across sectors, highly concentrated industries with a high tech component have the lowest median markup. This result holds both when comparing their median markup with the median markup of highly concentrated industries with a low tech component and when comparing it with the median markup of industries with a high tech component but low concentration. Figure 21 shows that the markup distribution for highly concentrated industries with a high tech component is bi-modal and with a very fat (high markup) tail. This would thus confirm the recent findings in the US literature, namely that at the top end of the distribution, some high tech/high concentrated sectors have high markups. However, contrary to the US findings, we do not observe a rising trend in these markups over our sample period.

Inspecting the data, therefore, and leaving aside issues of causality, there appears to be a case for saying that encouraging high-tech practices (as gauged by Manufacturing) raises productivity and (median) markups.

²⁹ Note that for the high tech sectors we combined the high and medium-high tech sectors as defined by Eurostat, see [Appendix D](#).

TABLES AND FIGURES

Table 1: Literature overview: US

Study	Period	Approach	Results
Markup developments			
Nekarda & Ramey (2013)	1980-2013	Sectoral (New Keynesian)	↑ 0.96 (1980) to 1.07 (2013)
De Loecker & Eeckhout (2017)	1960-2014	Micro: CompuStat (Production Function (PF), Cost-of-Goods-Sold (COGS))	↑ 1.18 (1980) to 1.67 (2014)
Traina (2018)	1950-2016	Micro: CompuStat (PF; COGS+Selling, General and Administrative Expenses(SGA))	↔ 1.1 (1980) to 1.16 (2016)
Eggertsson, Robbins & Getz Wold (2018)	1970-2015	Aggregate (New Keynesian)	↑ 1.04 (1980) to 1.2 (2015)
Hall (2018)	1988-2015	Sectoral (PF)	↑ 1.12 (1988) to 1.38 (2015)
Firm concentration developments			
Peltzman (2014)	1963-2007	<i>HHI</i>	↑ since 1982
Grullon et al. (2017)	1972-2014	CR_4 and <i>HHI</i>	↑ since 1997; > 75 % of industries saw increase
Autor et al. (2017 <i>a</i>)	1982-2012	CR_4 , C_{20} and <i>HHI</i>	↑ across sectors
Philippon et al (17)	1995-2015	CR_4 and <i>HHI</i>	↑ across indicators

Table 2: Literature overview: Europe

Study	Period	Approach	Results
Markup developments			
De Loecker & Eeckhout (2018)	1980-2016	Micro: CompuStat (PF, COGS)	global: \uparrow 1.1 (1980) to 1.6 (2016); Europe: \uparrow 0.98 (1980) to 1.64 (2016))
Calligaris et al. (2018a)	2001-2014	Micro: Orbis (PF, COGS)	global: \uparrow 4-6 % between 01-14
Díez et al. (2018)	1980-2016	Micro: Orbis (PF, COGS+SGA)	AE: \uparrow 39%; less evidence for EMEs
Canton & Thum-Thysen (2017)	2006-2013	Sectoral (PF, prof. services)	EU13: \downarrow 10-20%
Deutsche Bundesbank (2017)	1996-2014	Sectoral (PF)	EU7: \downarrow in less R&D intensive industries, no clear trend in other
Weche & Wambach (2018)	2007-2016	Micro: Orbis (PF, COGS)	EU28: \longleftrightarrow during crisis; levels clearly above US
Firm concentration developments			
Dotting et al. (2017b)	1995-2015	CR_4 and HHI	EU: \longleftrightarrow
Deutsche Bundesbank (2017)	2000-2012	C10 and HHI	DE, IT, FR: \longleftrightarrow
Valetti et al. (2018)	2010-2015	CR_4 and HHI	EU5: \longleftrightarrow

Table 3: Investment and Concentration: Regression Evidence

CR_{4t-1}	0.240*** (-5.85)	0.261*** (-6.07)	0.262*** (-6.03)	0.262*** (-4.63)
$(CR_{4t-1})^2$	-0.236*** (-5.76)	-0.254*** (-6.03)	-0.254*** (-5.99)	-0.254*** (-3.43)
Fixed Effects				
Country	N	Y	Y	Y
Year	N	N	Y	Y
Trim (90%)	N	N	N	Y
R^2	0.268	0.348	0.349	0.337

Note: '***' indicates significance at the 1% level. Numbers in parentheses indicate standard errors.

Table 4: Research and Development Comparisons (2000-2015)

	R&D	Researchers	High-tech Exports	Barriers to Entrepreneurship* Admin Burdens on Startups
	(% GDP)	(Mill)	(% of manufactured exports)	
Germany	100	103	74	128
France	79	96	115	132
Italy	45	44	35	101
Spain	45	67	32	145
United States	100	100	100	100

Notes: * Barriers to entrepreneurship and Admin Burdens from OECD over sample 1998, 2003, 2008, 2013 (US average=1.69, 1.50)

Sources: World Bank Indicators, US (average reference values=2.7%, 3963 per Mill, 21.4%).

Figure 1: CR_4 evolution over the period 2006-2015

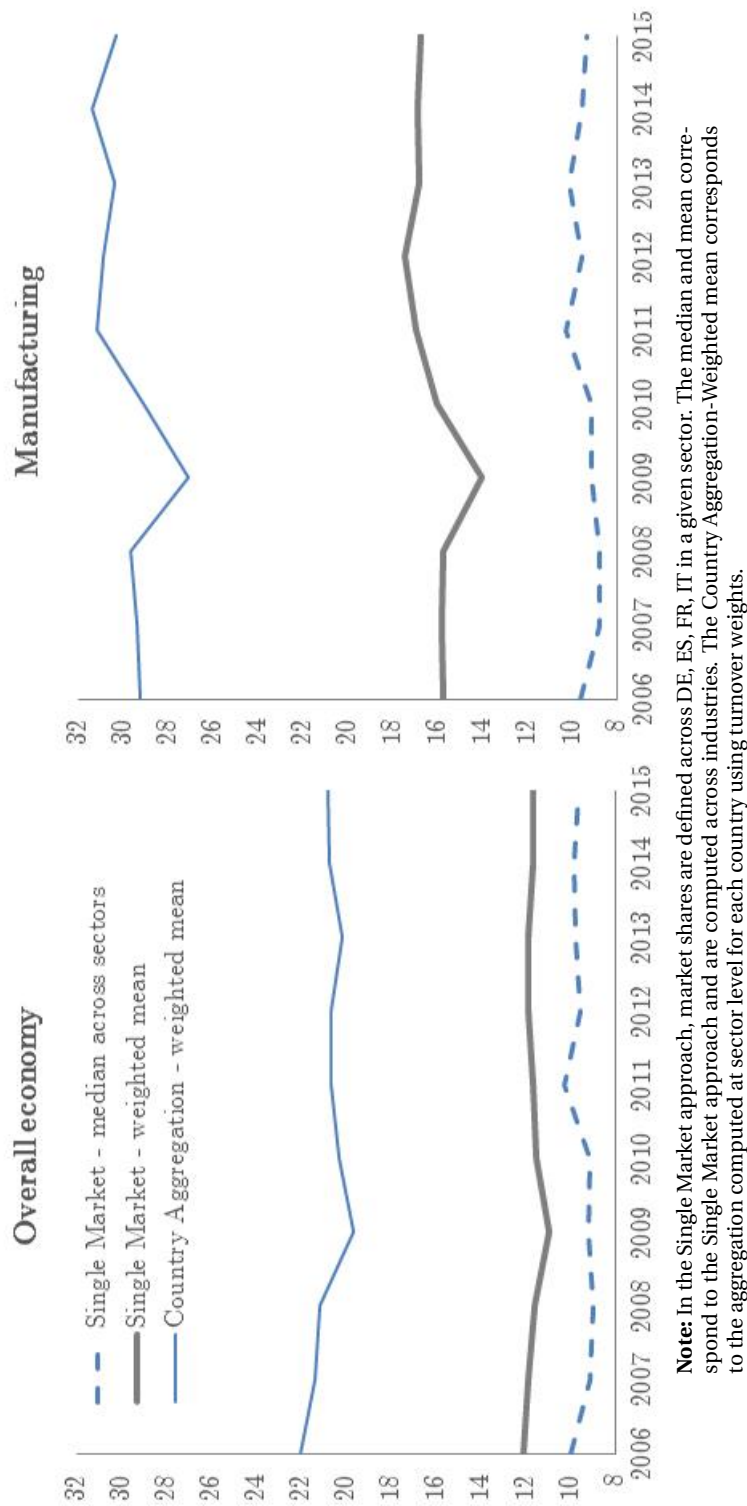


Figure 2: CR_4 evolution over the period 2006-2015 by country

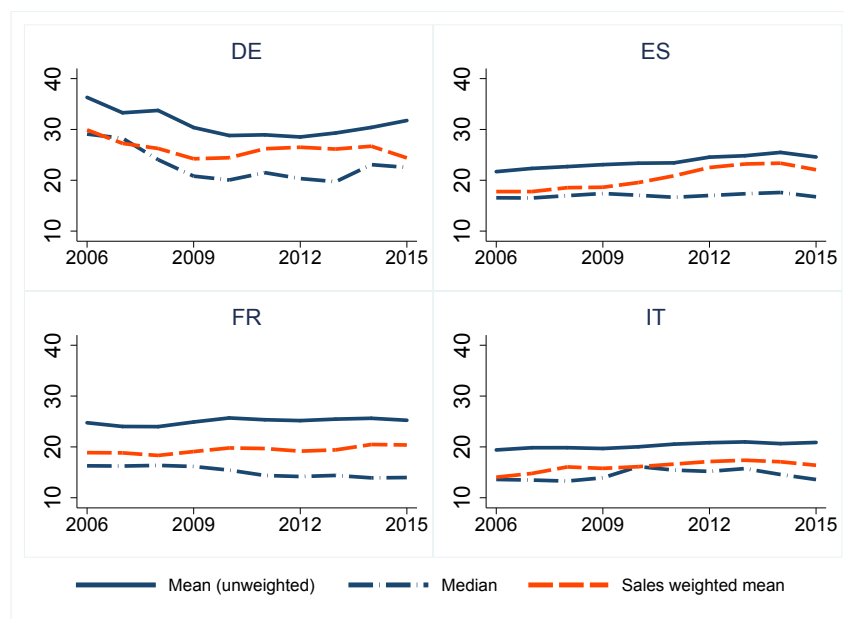


Figure 3: CR_4 evolution over the period 2006-2015 by country: Manufacturing

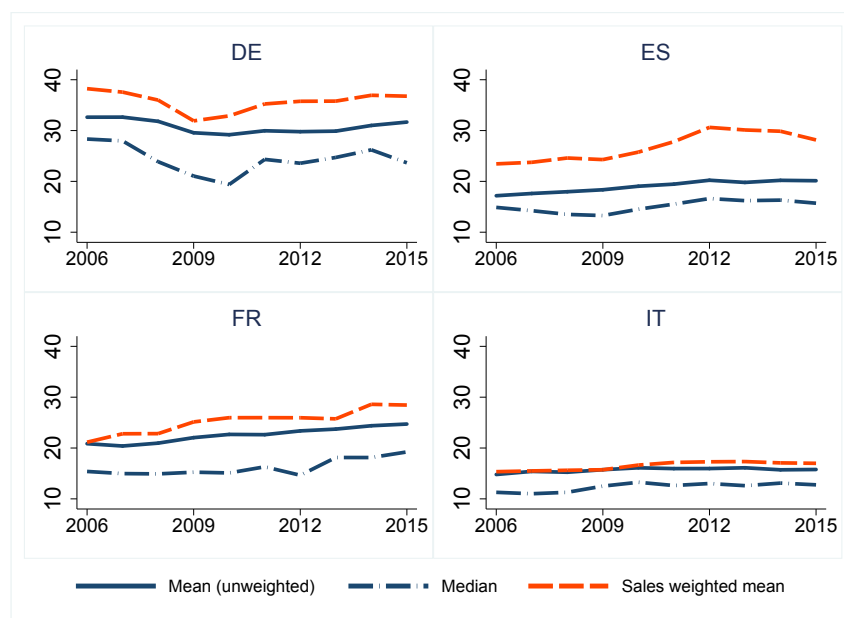
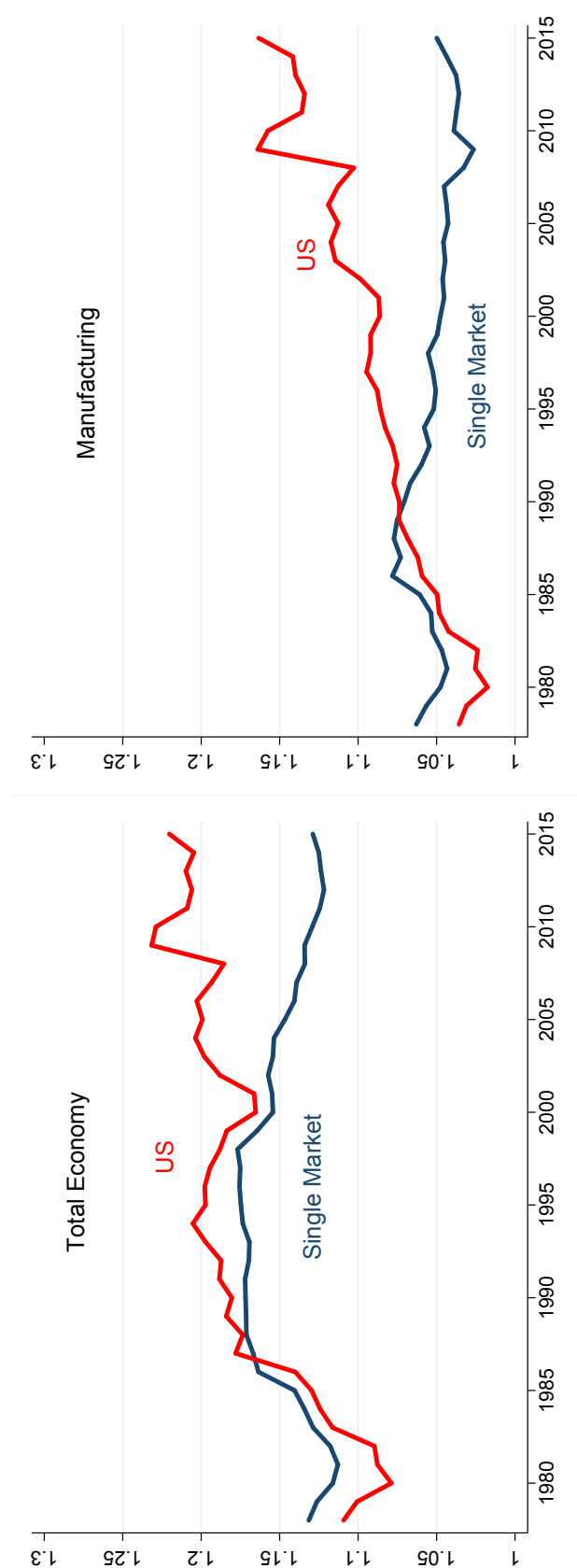


Figure 4: Markup evolution based on sectoral data



Note: The markup is obtained as the ratio between output and labour and material costs. Sectors are aggregated using output weights. Estimates based on EU-KLEMS data.

Figure 5: Markup evolution based on sectoral data (by countries)

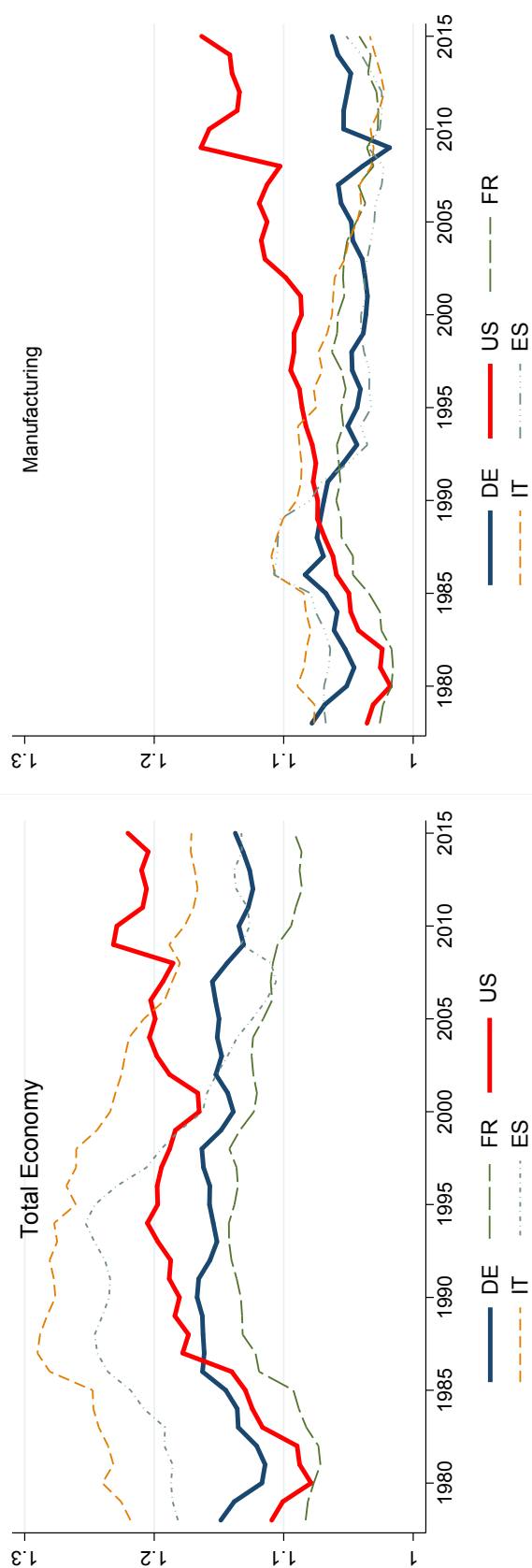
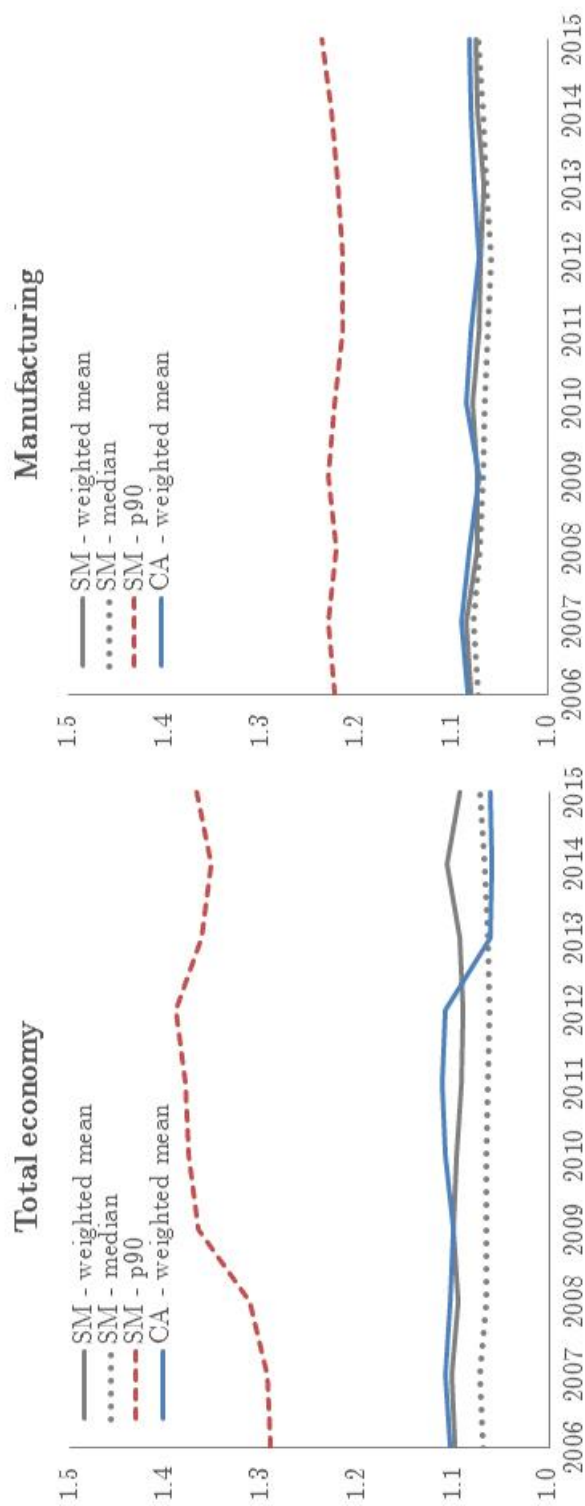


Figure 6: Markup evolution (Micro Data)



Note: The markup is the ratio of sales to variable costs. Variable costs include labour costs, external supplies, intermediate costs and taxes on products for IT and FR. For DE and ES, variable costs do not include taxes on products. SM- p50 and SM - p90 across sectors correspond to the SM approach and are computed for each sectoral distribution and then aggregated using sectoral turnover weights. SM- weighted mean is obtained by first aggregating firms at the sectoral level using market shares, and then sectors using sectoral turnover weights. The CA- country aggregation corresponds to the weighted mean of markups computed at sector level for each country using turnover weights.

Figure 7: Evolution of Micro Markup: Weighted Mean markup versus Markup of CR_4 firms.

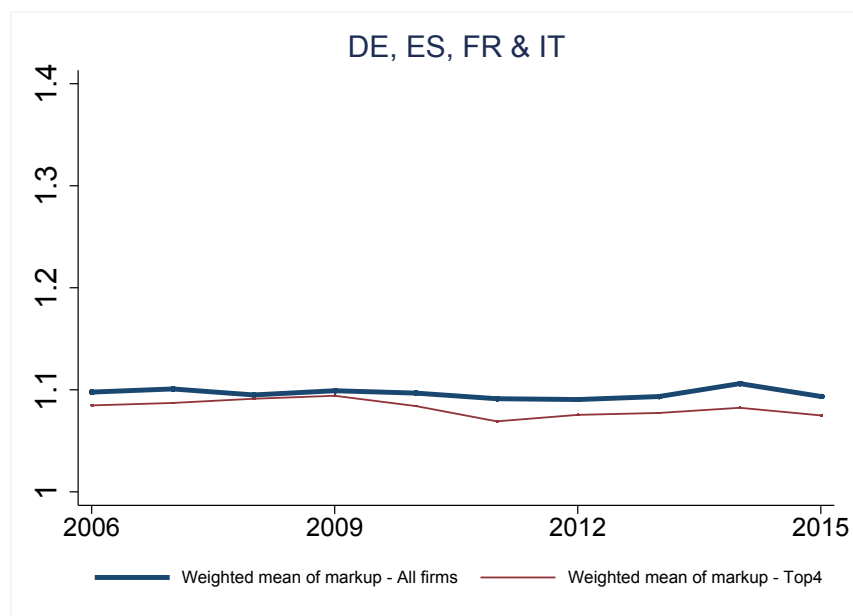
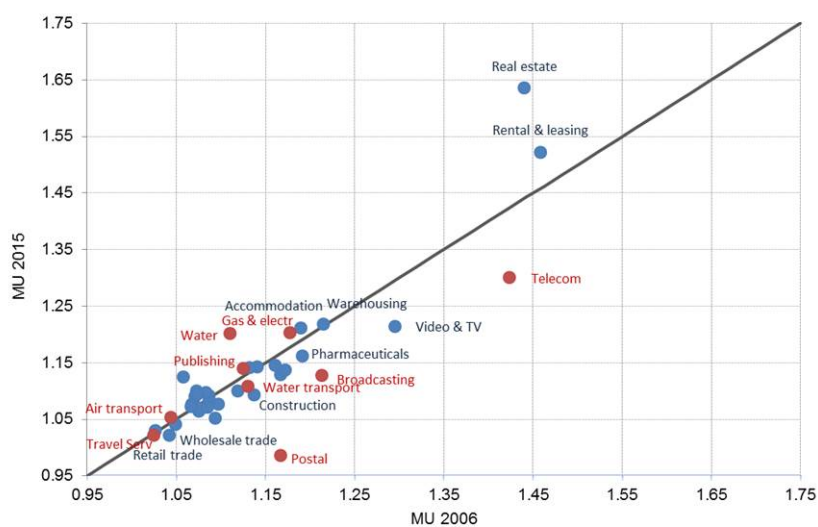
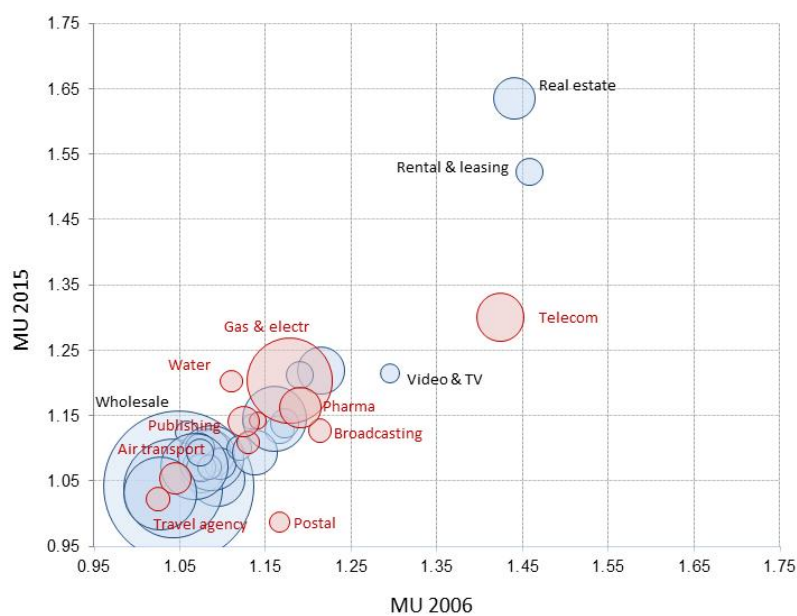


Figure 8: markup evolution across sectors with high and low concentration I



Note: The Red dots indicate most concentrated sectors according to the CR_4 indicator computed in 2006 (sectors with above-mean concentration among all sectors).

Figure 9: markup evolution across sectors with high and low concentration II



Note: See notes to figure 8. The size of the bubbles represent the relative share of the sectoral turnover over total sales.

Figure 10 (from Autor et al. 2017b)

Figure 4: Average Concentration Across Four Digit Industries by Major Sector

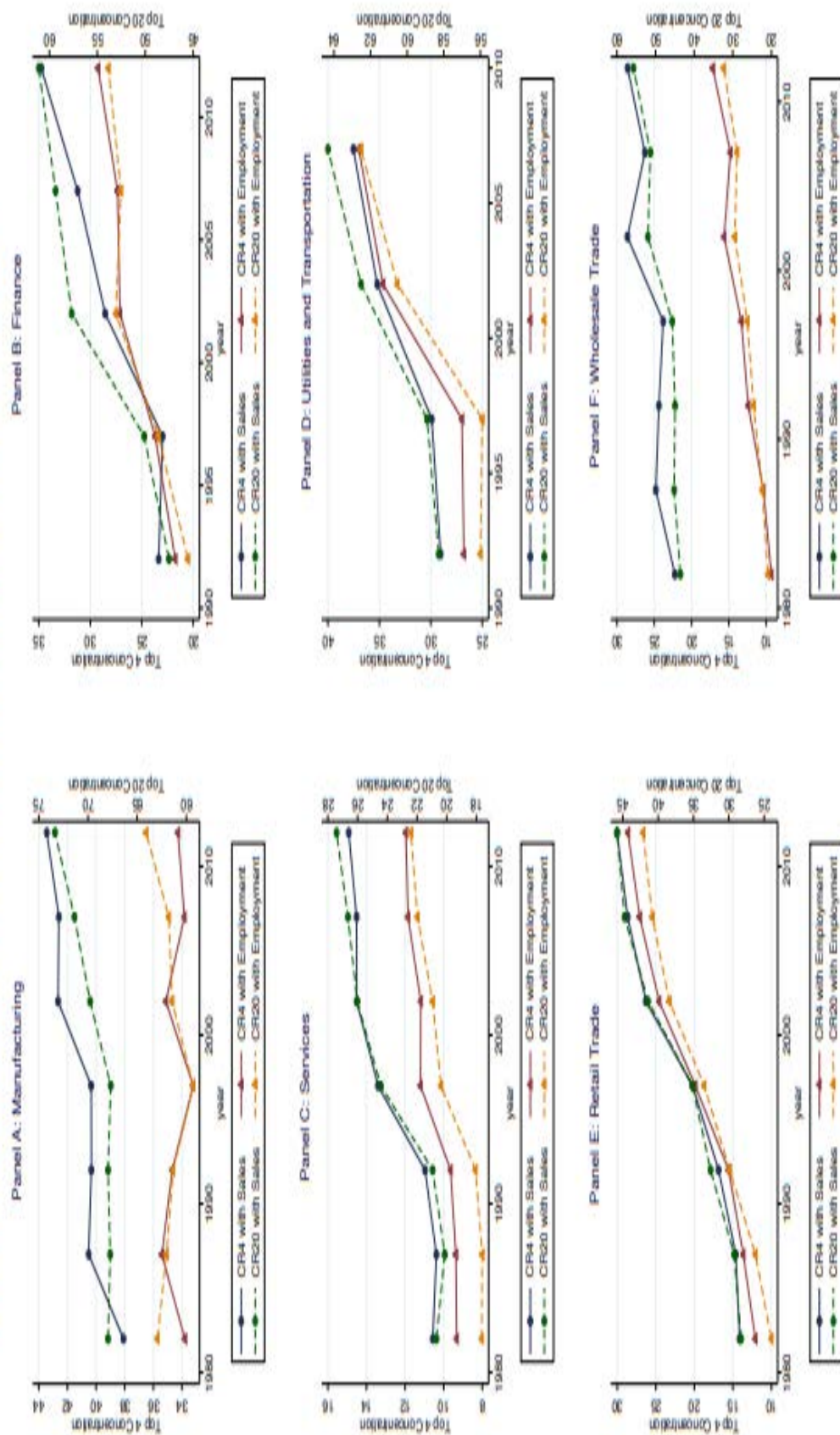


Figure 11: Concentration Ratios with Employment and Sales in the euro area

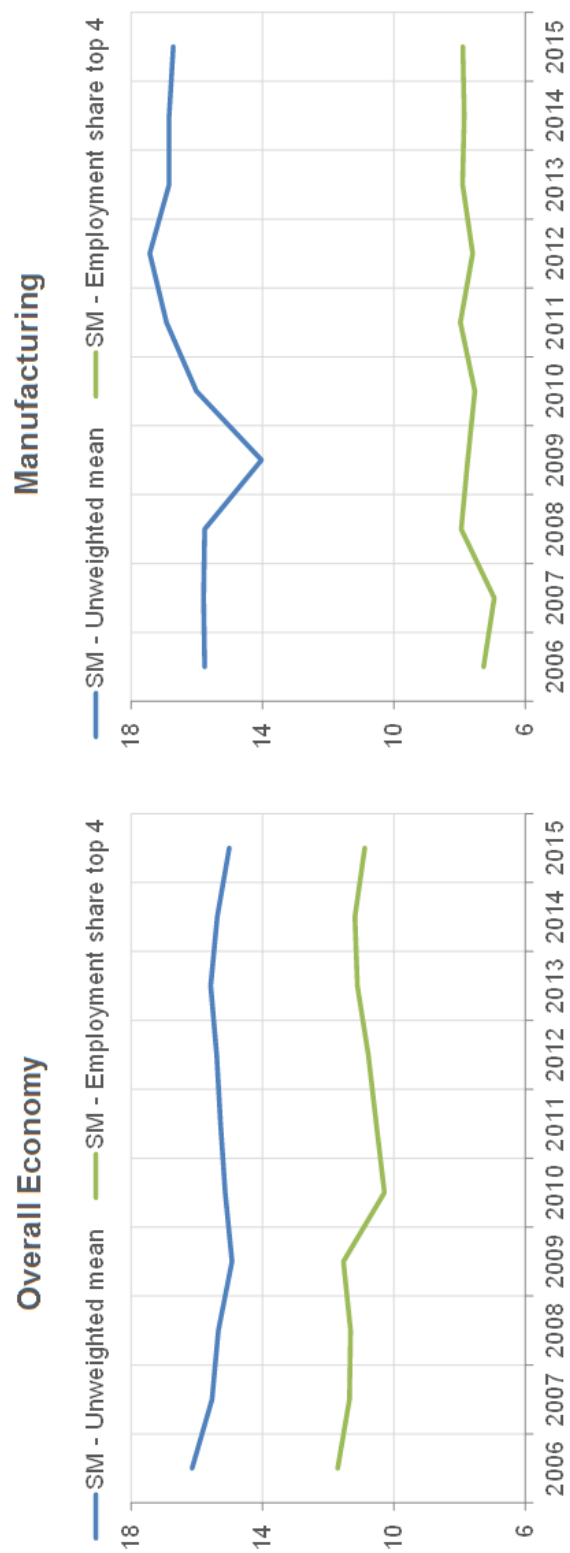


Figure 12: Concentration Ratios with Employment and Sales in the euro area (by macro sector)

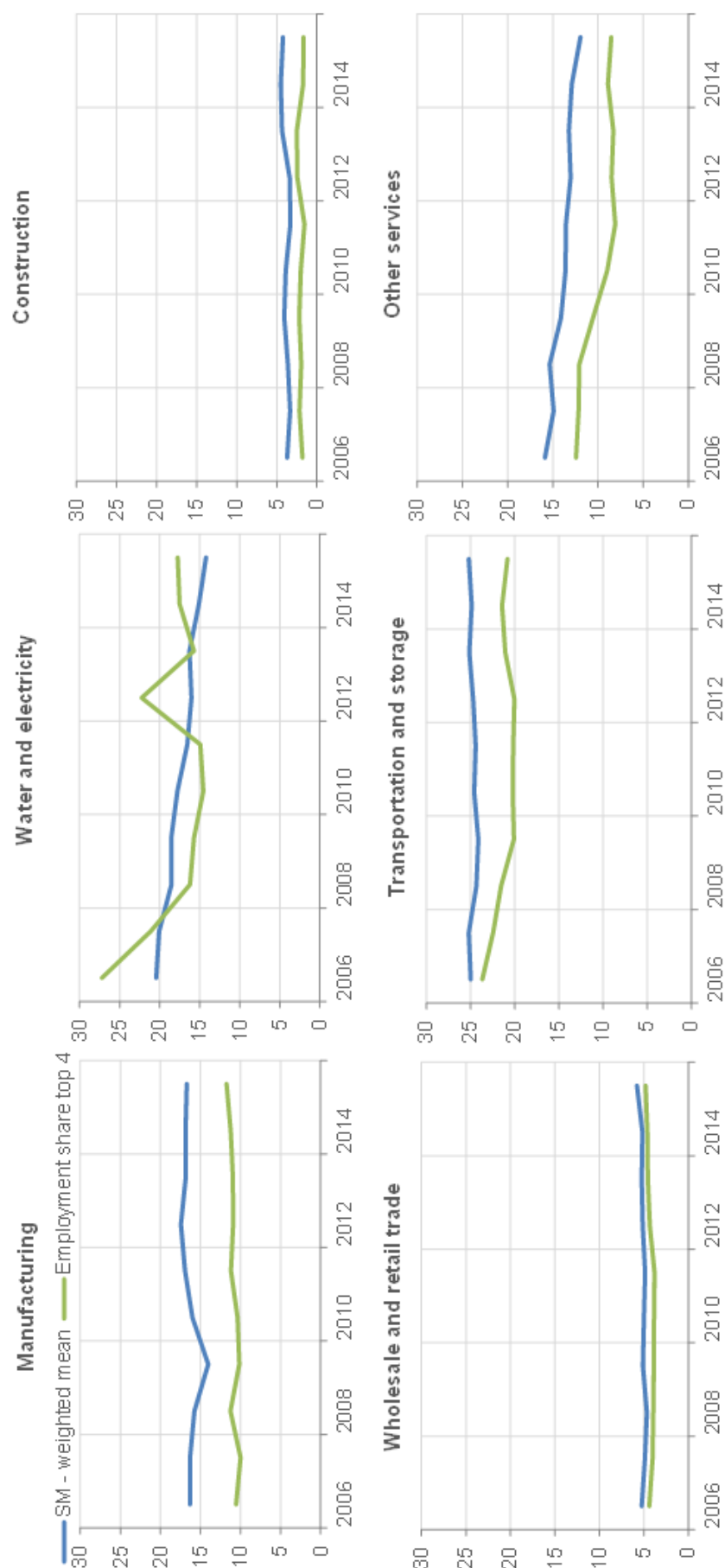
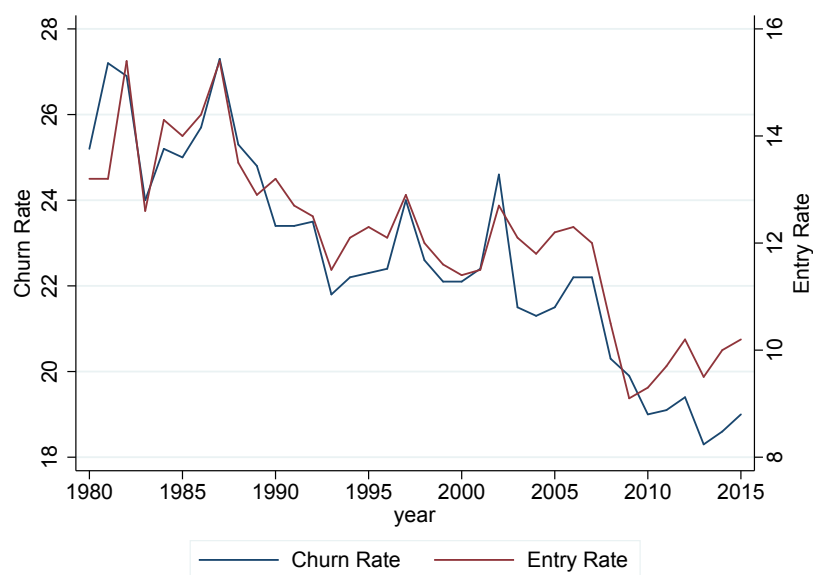
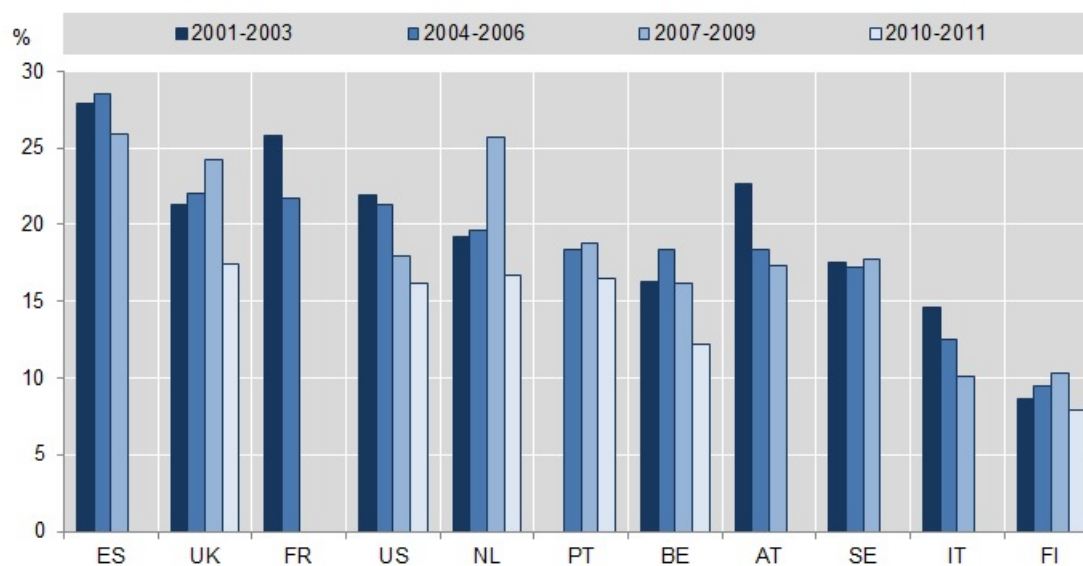


Figure 13: Establishment churn and entry rate in the US (%)



Source: US Bureau of the Census.

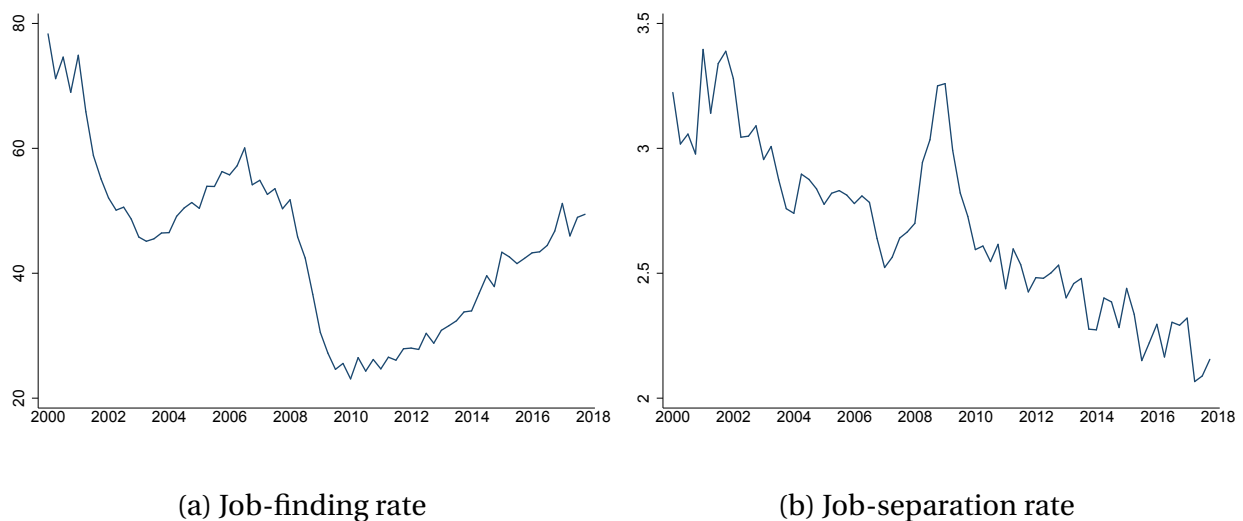
Figure 14: Startup rates across OECD countries (%)



Note: The graph reports start-up rates (defined as the fraction of start-ups among all firms) by country, averaged across the indicated three-year periods. Start-up firms are those firms which are from 0 to 2 years old.

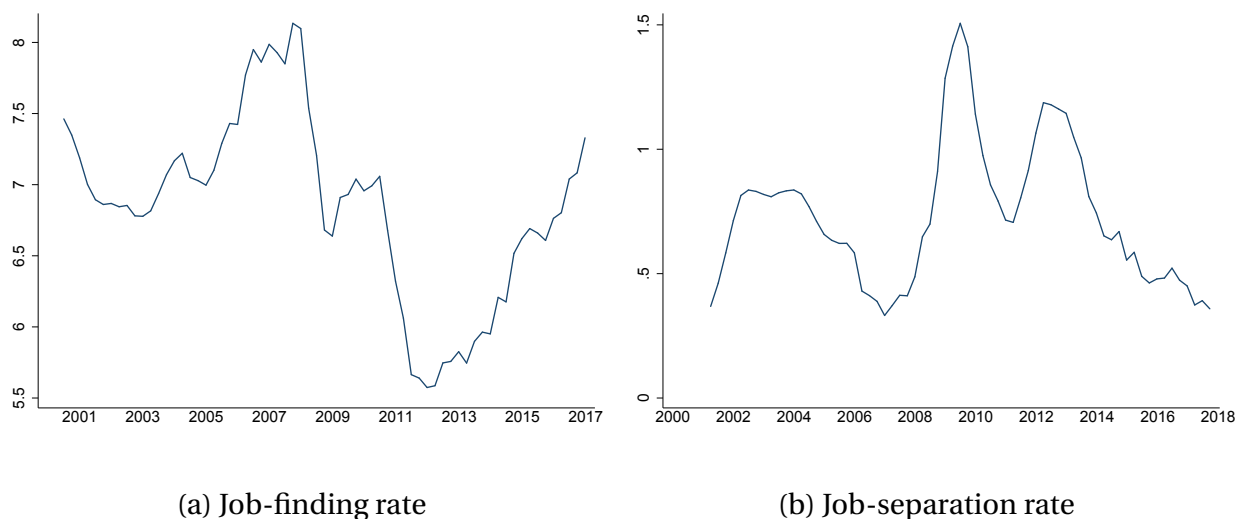
Source: Criscuolo et al. (2014).

Figure 15: Job-finding and job-separation rate in the US (%)



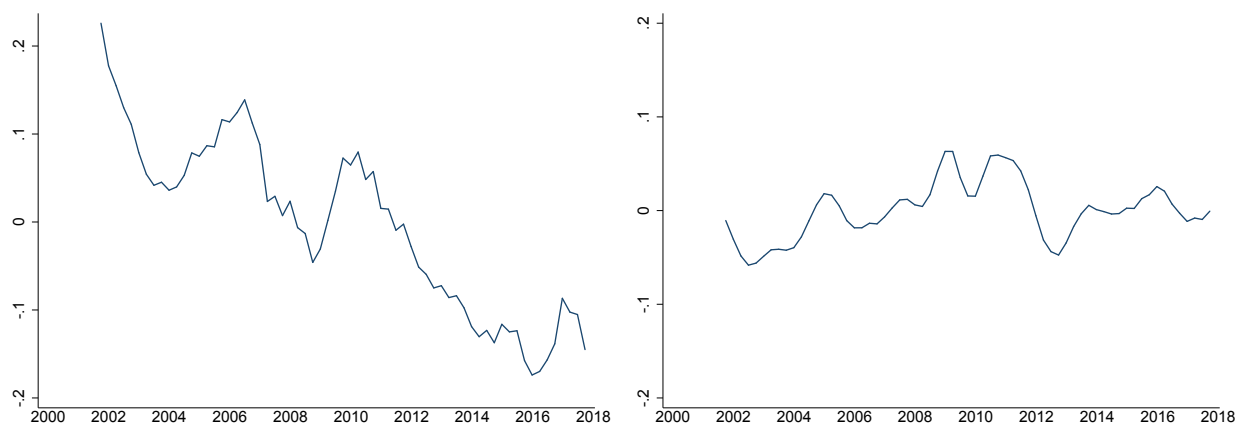
Note: Job-finding and separation rates estimated as in Shimer (2012*b*), using the redesign adjustment suggested by Elsby, Hobijn & Sahin (2013).
Source: BLS.

Figure 16: Job-finding and job-separation rate in the euro area (%)



Note: Job-finding and separation rates estimated as in Shimer (2012*b*), aggregated across durations using the optimal weighting method of Elsby, Hobijn & Sahin (2013).
Source: Eurostat.

Figure 17: Residuals from regressing the finding rate on unemployment



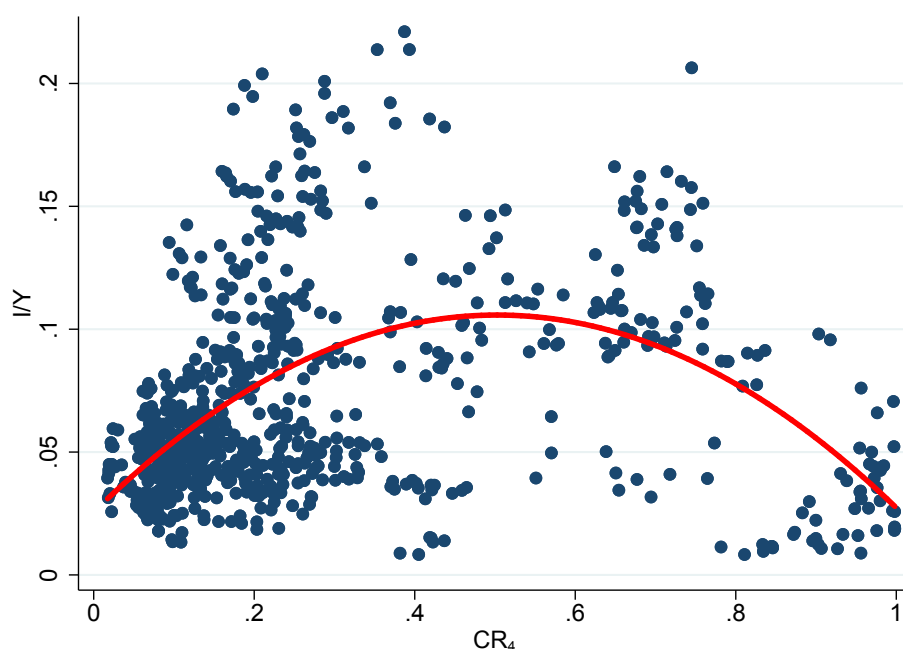
(a) Job-finding rate

(b) Job-separation rate

Note: The job-finding rates is estimated as in Shimer (2012b), aggregated across durations using the optimal weighting method of Elsby, Hobijn & Sahin (2013). The graphs show the 3 quarter moving average of the standardized residuals from a regression of the job-finding rate on the unemployment rate.

Source: BLS and Eurostat.

Figure 18: Investment Rate and Concentration



Note: In the Single Market approach, market shares are defined across DE, ES, FR, IT in a given sector. The median and mean correspond to the Single Market approach and are computed across industries. The Country Aggregation Weighted mean corresponds to the aggregation computed at sector level for each country using turnover weights.

Figure 19: Interaction between Concentration and TFP Growth

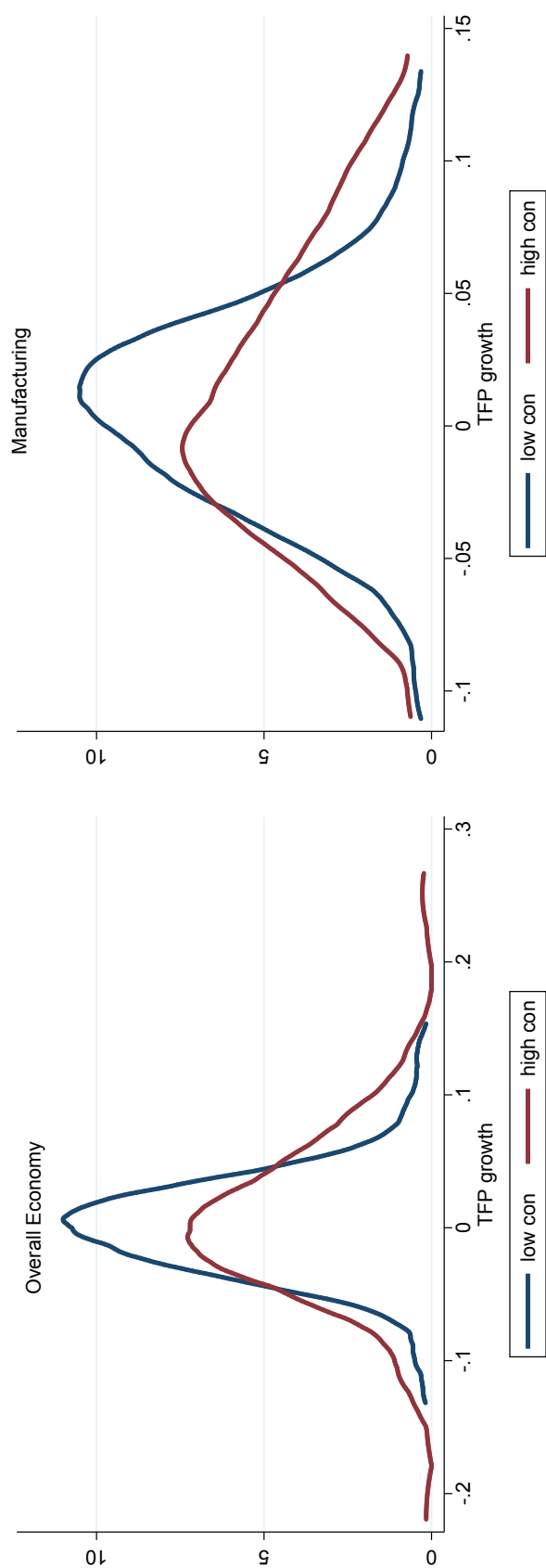


Figure 20: Concentration, TFP Growth and Technology in Manufacturing

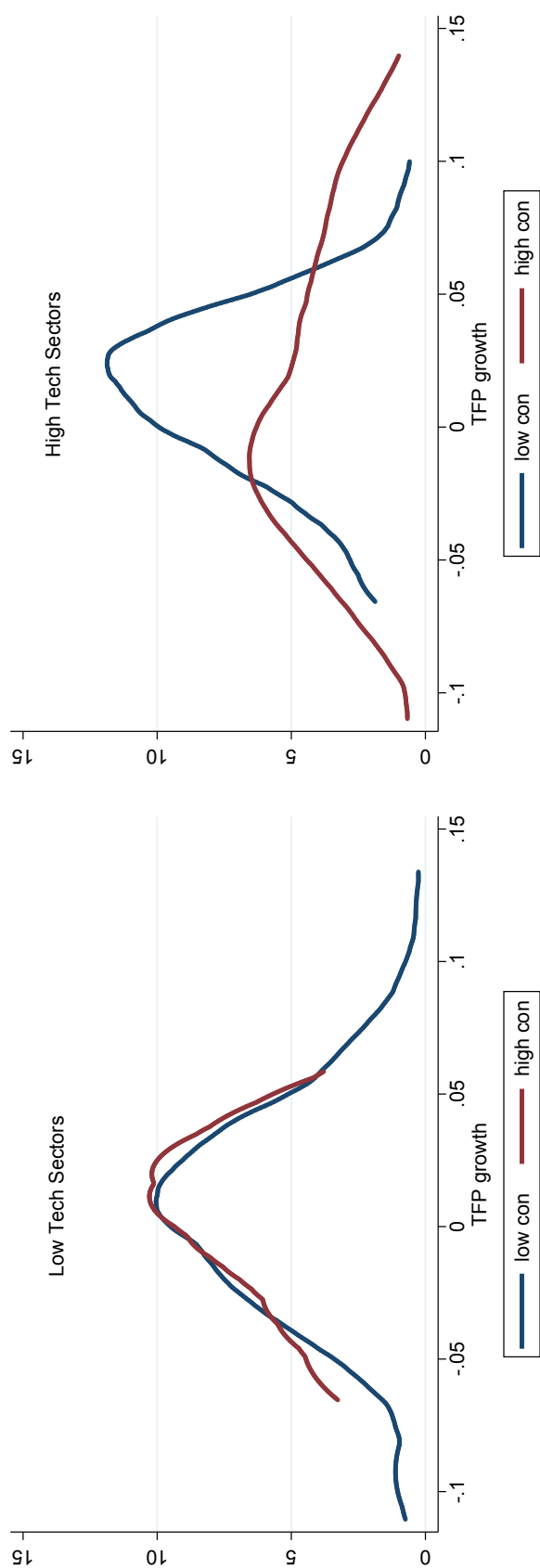


Figure 21: Interaction between the Markup, Concentration and Technology

