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# Estimating Markups in the Netherlands

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# 1 Introduction

In this study we analyse the dynamics of firm markups at a national level in the Netherlands. This document is a technical report that describes the literature review, data, methodology and results used in Meijerink et al. (2019) but also elaborates and extends the analysis.

This research is part of a series of papers in which the productivity slowdown and its possible causes for the Netherlands are analysed. A previous study (Grabska et al., 2017) finds that, as in many OECD countries, productivity growth in the Netherlands is slowing down. Subsequently, we analyse the dynamics of firms on the productivity frontier and laggard firms (See van Heuvelen et al., 2018 and Meijerink et al., 2018). We find no indication of divergence taking place between the most productive firms (frontier firms) and less productive firms (laggards) in terms of productivity over time.

In this report our attention turns to markups. An expanding body of studies estimates firm-level markups, defined as the ratio of output price over its marginal cost. Although the timing of the increase differs, most studies report a sharp increase in the average markup in the US and Europe (including the Netherlands), which is driven by firms located at the top of the markup distribution (i.e. De Loecker and Eeckhout, 2017, 2018; Calligaris et al., 2018; Diez et al., 2018). Since this increase is interpreted as an indication of the lack of competition between firms, it has sparked a discussion on the possible need for policy intervention.[1] Furthermore, the increase in markup is associated with a number of other trends, like the fall in the labour income share (De Loecker and Eeckhout, 2017; Autor et al., 2017b), underinvestment (Gutiérrez and Philippon, 2017a) and the growing share of intangibles (Haskel and Westlake, 2017).

The recent slowdown in productivity in the US has been linked to decreasing competition (De Loecker and Eeckhout, 2017), which may also apply to the Netherlands. Therefore, this paper assesses changes in the competitive environment of firms in the Netherlands, measured by changes in the markup. Most studies focus on a sample of very large firms (i.e. publicly traded firms). Smaller, often private firms are usually excluded due to data limitations. We use a large representative firm-level dataset to explore the development of markups in the years 2006-2016. Unlike other studies, we are able to study the development of markups of smaller firms. We closely follow the production function approach proposed by De Loecker and Warzynski (2012). This approach derives firm-level markups from the first-order condition that determines the cost minimizing level of a flexible input.

We derive the following main results. First, we show that the average (weighted) markup in the Netherlands has not risen over 11 years. We do find some evidence that markups are mainly increased by firms located at the upper end of the markup distribution. However, this increase is far below the magnitude found in other papers and is not driven by large firms. Second, average markups are estimated to be higher in service sectors than in

[1] See e.g. Financial Times, "Corporate power on the agenda at Jackson Hole", 17/8/2018.

manufacturing sectors. In addition, the dispersion is greater within service sectors, indicating greater markup heterogeneity between firms. Third, we find that large and small firms within a sector produce differently. The separate estimation of markups for each size group leads to higher (lower) markup levels for larger (smaller) firms. Finally, we use different setups to check the sensitivity of our results to methodological choices. We find that the main results are robust.

The rest of the paper is organized as follows. The next section discusses the relevant literature. Section 3 discusses the data and the construction of the variables. Section 4 describes the applied methodology. Finally 5 provides empirical results and discusses the implications.

# 2 Literature review

The literature review starts with establishing the link between competition and productivity. It then discusses the current literature on the developments in markups and competition.

## 2.1 Competition and productivity

The process of rivalry between suppliers that takes place either in or for the market is what we call competition. Firms compete to attract customers by offering, for example, more innovative, higher quality or lowered priced products. There is a large body of empirical evidence that shows that competition increases productivity. The evidence can be split up into two groups.

The first group of research exploits between market differences in the level of competition to examine the relationship between competition and productivity. Haskel (1991) finds for UK firms that high levels of market share and market concentration have a negative effect on Total Factor Productivity (TFP). Nickell (1996) shows for a sample of 690 British manufacturing firms that competition, measured by increased number of competitors or by lower levels of economic rents, is related to lower TFP growth. Disney et al. (2003) show for UK manufacturing firms that exit, entry and market share change accounts for the majority of productivity growth. They also find that competition is an important driver for within firm restructuring (i.e. adopting new technologies and organisational changes). Bourlès et al. (2013) analyse the effect of competition in the intermediate product markets on the productivity of downstream firms. They find that anticompetitive upstream regulations have lowered TFP growth particularly for the most productive firms. They estimate that increasing competition in upstream sectors could increase TFP growth by 1 to 1.5 percentage points per year. Measuring the degree of competition that a firm faces is difficult. Therefore, Tang and Wang (2005) use a survey-based approach asking firms to report the intensity of competition they face. Using this measure of perceived competition in a sample of Canadian firms, they find that firms that perceive higher competition tend to have higher productivity levels.

The second group of research looks at (exogenous) differences in the level of competition within a market and the effects it has on productivity.[2] Maher and Wise (2005) show that the liberalisation and reforms that increased competition in the UK utilities sector led to high productivity growth rates. Both liberalisation of the road freight in OECD countries and the deregulation of the US telecom sector led to productivity gains (See Olley and Pakes, 1996; Boylaud, 2000). Gort and Sung (1999) show that between 1985-1991 TFP growth rates are between seven to fourteen times higher in competitive US telecoms markets than in regional monopolies. Jamasb et al. (2005) summarize research on the impact electricity reforms (i.e. privatization and liberalization) for a number of countries providing evidence of productivity gains following reform. On the relationship between competition and

[2] Pilat (1996) argues that effect of competition on productivity have been revealed most clearly by the effects of deregulation.

productivity, Holmes and Schmitz, (2010) give an overview of the literature of industries that have seen a change in their competitive environment. They conclude that nearly all studies show that increased competition increases productivity and many studies show that firms facing increased competition made substantial investments to raise productivity.

The effect of introducing regulation that decreases competition has been shown to influence productivity negatively. Haskel and Sadun (2012) look at the effect of introducing new regulations in the retail sector in the UK, specifically the impact of a 1996 regulatory change that increased the costs of opening large stores. The subsequent fall in shop size lowered TFP growth by 0.4% per year. Cincera and Galgau (2005) find that regulation discouraging entry in European markets led to higher markups and lower productivity growth.

Clearly the empirical literature suggests a positive relationship between competition and productivity levels and growth. The literature proposes a number of mechanisms that are behind this relationship, of which three will be discussed.

The first mechanism is that competition is a disciplining device. Competition forces firms to become more efficient as inefficient firms are forced out of business. Bloom and Van Reenen (2010) and Bloom et al. (2012) find a positive relation between the strength of management practices and product market competition. Strong competition boost average management practices by the elimination of badly managed firms and pushing firms to improve their practices.

The second mechanism is that competition ensures that more productive firms gain more market share at the expense of less productive firms. For example, Syverson (2004) shows that in ready-mix concrete industry in the US more competitive geographic market often have a smaller tail of less productive firms. This supports the idea that in a competitive market the least productive firms exit. In addition, several studies show that productivity growth is largely driven by reallocation from less to more productive firms than within firm improvements (See Arnold et al., 2011; Baldwin and Gu, 2006; Disney et al., 2003; Nicoletti and Scarpetta, 2003.)

Thirdly, competition drives firms to innovate. The relationship between innovation and productivity is more complex. Competition is a strong incentive to innovate. However, the incentive to innovate comes from the ability of firms to generate positive returns from successful innovations, which suggest the need for ex-post market power. Therefore, a combination of competition and market power (e.g. intellectual property rights and patents) play a role in innovation.

Griffith et al. (2010) find that increased competition that was introduced by the single market programme in Europe in the early 1990s spurred innovation. Aghion et al. (2005, 2009) find evidence of an inverted-U shape relationship for UK firms between competition and innovation. At first increased competition leads to more innovation, but at a certain point there is too much competition which leads to less innovation. Correa and Ornaghi (2014) apply a similar framework as Aghion et al. (2005) to US manufacturing data and find a positive relationship between competition and innovation. Patent counts are found to increase with more competition. Also productivity is found to increase when moving from less to more competitive industries. Correa and Ornaghi (2014) suggest that when intellectual property rights are well defined, increased competition will lead to higher levels of innovation spurring productivity. Aghion et al. (2015) also find evidence that strong patent rights complement competition-increasing market reforms to induce innovation. Gutiérrez and Philippon (2016) argue that firms underinvest as a result of decreased competition, leading to lost productivity potential over time.

## 2.2 Recent developments in markups

The recent literature provides ample evidence that markets in the US have become more concentrated and competition has weakened since the 1980s (see Autor et al., 2017b; Gutiérrez and Philippon, 2016, 2017). Furthermore, De Loecker et al. (2018a) find evidence that the markups of publicly traded firms have risen from 21% in 1980 to 61% in 2016.[3] The rise in markups occurs in the period 1980-2000 and after 2011. This sharp rise is exclusively due to a sharp increase by firms located in the top decile of the revenue weighted markup distribution. Azar et al. (2017) find evidence that labour demand in the US is highly concentrated, giving firms buying power which leads to declining posted wages. Barkai (2018) documents that the decrease in the labour share of value added in the US was combined with an increasing profit share over the last 30 years. In sum, evidence seems to indicate a decrease in competition in the US.

The situation in Europe seems different where markets are less concentrated and firms have lower excess profits and face lower regulatory barriers to entry. Therefore, European markets are arguably more competitive than their American counterparts (see Gutiérrez and Philippon (2018)). Nonetheless, De Loecker and Eeckhout (2018a) show that the markups have also risen in Europe. This is the only study that reports results for the Netherlands. The Dutch markup is estimated to have increased from 5% in 1980 to 52% in 2016. This is, by all standards, a rather large increase of 47% points. However, this increase remains somewhat below the European average increase of 66% points, which is similar to the estimated increase for the United States. Important to note is that most of this increase happened, certainly for the Netherlands, after 2012.

Diez et al. (2018) find similar results for advanced economies (including the Netherlands) as De Loecker and Eeckhout (2018a), using the same dataset. Diez et al. (2018) estimate a GDP-weighted average and find increasing markups of 39% since 1980 for advanced economies. Although no revenue weighted markups are shown for any country other than the US, they state that the markups in Europe have increased mainly since the 2000s. They show that the distribution of markups, which are highly concentrated around 1 in the 1980s, becomes less

[3] De Loecker and Eeckhout (2017) measure the costs of the flexible input by the cost of goods sold. Both Karabarbounis and Neiman (2018) and Traina (2018) extend this measure with selling, general and administrative expenses and show that the average markup is relatively flat over time. Karabarbounis and Neiman (2018) point out that the shift from costs of goods sold to selling, general and administrative expenses is in line with the increasing importance of intangible assets in production. De Loecker and Eeckhout (2018b) argue that selling, general and administrative expenses are not variable but fixed costs and are therefore used incorrectly in the analysis of Karabarbounis and Neiman (2018) and Traina (2018).

concentrated in 2016 as the right tail gains a lot more mass.[4] The increase in markups is therefore driven by high markup firms.

Calligaris et al. (2018) find that the average markup increased over 2001-2014 for 26 countries (for 21 OECD countries including the Netherlands). Important to note is that Calligaris et al. (2018) report the unconditional average (log) markup and not revenue weighted markups, as in the other papers. The average increase is smaller, around 6% over a shorter time period of 13 years. The increase in the mean markup only starts after 2005. This trend is driven by firms at the top end of the unweighted markup distribution that show an increase of around 25%. Interestingly, they find that digital intensive sectors have higher markups than less digital intensive sectors.

Weche and Wambach (2018) analyse the markup for 17 EU countries over 2007-2015.[5] Contrary to the previous papers, they find that the average weighted markup hardly increases over this time period. The markup first drops during the crisis, followed by a post-crisis increase. However the European markup in 2015 has not reached its pre-crisis level. This is in sharp contrast to the US where the markup quickly recovers to reach its pre-crisis level before 2011 (see De Loecker and Eeckhout, 2017). This could be attributed to the fact that Europe was hit by a second crisis (European Debt Crisis). Weche and Wambach (2018) state that deleting the bottom and top 1% of the markup distribution is crucial for the result.[6] Considering that the markup rise in other papers is caused by the top decile and the focus is on the mean value, which is sensitive to outliers, this result is of importance. Weche and Wambach (2018) conclude as follows:

*“As markup figures for Europe are very much different from those in the United States, one should be cautious by transferring arguments in this debate from the United States to Europe”*

The study most closely related to our work is that of De Loecker et al. (2018b), where the markup of another small open economy, Belgium, is estimated over 1980-2016. Crucially, they state that the results of De Loecker and Eeckhout (2018a) should not be trusted at face value for Belgium due to the small number of firms (i.e. 80 firms). The research stresses the importance of using a free variable to estimate the output elasticity. They make a distinction between service material inputs and goods material inputs, arguing that the latter is free and the first is more fixed. Although they initially find decreasing markups for total material inputs, using only goods material inputs as free inputs leads to rising markups for the top of the distribution. This distinction is crucial as the service material cost share is increasing over time leading to decreasing markups. Importantly, they find no evidence of rising markups after the early 2000s for Belgium, the rise in markup is before this period.

[4] What also becomes evident is the existence of extremely high markups which were non-existent before 2016. In the markup distribution of 1980, values higher than 3 do not exist, while in 2016 the distribution still has mass until the value of 10. This indicates the rise of extreme markups or measurement errors.
[5] The sample includes only firms with revenue of at least 2 million EUR in at least one year. The Netherlands is not included in the sample because fewer than 100 observations were available for at least one year after the selection.
[6] Weche and Wambach (2018) state that they cannot rule out that this exclusion underestimates the real average markup, even though a markup value of more than 400,000 seems rather unlikely. Also the truncation of the distribution is generally applied in the literature. For example both De Loecker and Scott (2016) and Calligaris et al. (2018) delete the top and bottom 3% of the markup distribution.

The differences in weighting, time period, and presentation of results make it difficult to compare between the studies. However, most claim to find similar results, increasing markups driven by the high markup firms. Increasing markups in the top decile of an unweighted distribution do not have the same implications as that of a weighted markup distribution. In the latter case, large firms are driving the results, while this cannot be said in the first case. This is a subtle but important difference.

Calligaris et al. (2018) rightfully raise the question whether it is the same firm that charges high markups over time. The superstar firm hypothesis implies some sort of persistence, as firms that benefit from globalization and technological progress remain the most productive. If it is found that firms that charge high markups are not the same firms over time, it is not so clear what rising markups in the top decile are really indicating.

The decreased competition (i.e. higher markups) is not necessarily the result from relaxing anti-trust rules or stricter regulation, but could be due to sectors becoming more “winner takes most/all” following globalization and/or new technologies (Van Reenen, 2018). Autor et al. (2017a) present a model in which only the most productive firms can benefit from the advantages of globalization or technological change. In this model, market concentration increases following the rise of superstar firms that have high profits and a low share of labour costs in firm sales. Autor et al. (2017b) provide empirical support for their model, confirming that concentration of sales within industries has increased and that the labour share has declined the most in the industries in which concentration increases have been the greatest. As aggregate labour productivity is often weighted by firm employment this trend will lead to less growth in labour productivity as the most productive firms use less labour. However, how this trend leads to a decline in aggregate TFP growth is less clear as aggregate TFP is often weighted by firm revenue. In fact, the revenue weighted average TFP should grow as super productive firms gain more market share.

It is also important to note that an increase in markups does not per definition imply higher profits. Karabarbounis and Neiman (2018) argue that increasing markups might be caused by a rise in fixed costs. Since markups only include the difference between marginal costs and the output price, fixed costs are left out of the formula. A higher markup might be needed to recover higher fixed costs. For example, rising rents and higher investments in information technology are not variable costs. However, De Loecker and Eeckhout (2017) and Barkai (2018) contest this claim by showing that the increased markups are associated with higher profits and market values of US firms.

# 3 Data

## 3.1 Introduction

The data used in the analysis are obtained by combining three datasets obtained from Statistics Netherlands (or CBS Central Bureau of Statistics). Firstly, the ABR (business registry) dataset, which contains information on important events in the life-cycle of the firms and some basic background statistics such as firm birth date, sector and size; secondly, the NFO (non-financial firms) dataset, which contains book value data of Dutch firms; and thirdly, the Polisbus dataset, which contains employee level data and is used to construct the labour hours variable. Each dataset is briefly discussed below.

### 3.1.1 ABR

The ABR dataset spans the period 1994 to 2016. During that period, changes were made in terms of definitions and the way firm data is obtained over time.[7] Due to major changes in the ABR in 2006, we only use the data from 2006 onwards.[8] We also exploit the event database of the ABR. The events database shows the events (a merger, acquisition, restructuring, termination, birth, etc.) that have taken place at a firm or enterprise level. Multiple events may happen within a year.

We tried using the number of employees from the ABR as a proxy for labour input but decided against this for three reasons. Firstly, there are slight but multiple changes in the definition over the sample period that lead to level shifts. Secondly, this variable is reported in rounded integer values of the fulltime equivalent number of employees. This might be a good approximation for large firms but is problematic for small firms. Thirdly, before 2006 changes in number of employees hardly appear in the data as these mutations are rarely reported by firms to the chamber of commerce. Therefore, the initial number of employees often remains unchanged within this period, giving an inaccurate indication of individuals working for the respective firm.

[7] The main changes that have taken place in de ABR are as follows. Before 2006, the ABR was based on the registry from the chamber of commerce. As a consequence, firms not obliged to register did not appear in the ABR. This mainly affected firms located in the agricultural, governmental and health sectors and part of the business services sector. After 2006, the BBR (*Basis Bedrijven Register*) became the backbone of the ABR. The BBR obtains input from both the chamber of commerce and the tax authorities. As a result, firms not obliged to register at the chamber of commerce but did pay vat, payroll tax, etc. do appear in the ABR.
In 2009, the economic classification of firms changed from SBI1993 to SBI2008. For a few years after the change, both definitions were retained. In 2010, Statistics Netherlands made the transition to the use of the OG-plus algorithm, which led to the bundling of both definitions on the basis of information from the trade registry and the business registry of the tax authority. The major implication of this transition is that an enterprise can only consist of one firm with the notable exception of the largest 2200 firms. After 2014, the NHR (Nieuwe Handels Register) and the Chamber of Commerce register form the backbone of the ABR. The obligation to register has been significantly expanded for certain sectors and only a few exemptions from business registry remain.

[8] The major change in de ABR in 2006 leads to a very large influx of new firms for this year and a large increase in firm deaths in the year before. Contrary to popular belief, the firms that died and re-entered in 2006 are often not the same firm. For example, there are large changes in the number of employees working for a firm in 2006 as the mean increase in number of employees is 13%, while in the years before and after 2006 it is only 3%.

### 3.1.2 NFO

The NFO data are obtained from two different sources. For large firms, surveys are used and for smaller firms, tax information (*vennootschapsbelasting*) obtained from the tax authority is used. The NFO data span the period 2000 to 2016. The NFO data are, in Statistics Netherlands terminology, at the enterprise level. An enterprise can contain multiple firms. In most cases, however, the enterprise is equal to one firm.[9]

### 3.1.3 Polisbus

A proxy for labour input is obtained using the dataset Polisbus.[10] The Polisbus dataset spans the period 2006 to 2017. The data contain a long list of variables related to the employment of individuals who work and pay taxes in the Netherlands. We use the number of payed hours that an individual works for a certain firm. This includes the contract hours and the extra payed hours; non-working contract hours due to furlough or sickness are included in this measure.

## 3.2 Merging the datasets

The NFO dataset is at a higher level of firm aggregation (enterprise level) than the Polisbus data (firm level). After 2010, however, the distinction between the two no longer exists except for large enterprises. But also before 2010, most enterprises consist of only one firm. The larger the enterprise, the more likely that it consists of multiple firms. We use the ABR registry to match the enterprise level to the firm level. We have data for 2006 to 2016.[11]

A small share (around 2.7%) are firm-year observations for which some of the firms that are part of an NFO enterprise do not have corresponding employee data in the Polisbus.[12] For these cases there is a partial match (i.e. some firms that are part of an enterprise do have employee data while other firms do not). We deal with partial matches by using the information available in both datasets. As an example: say there are four firms (A, B, C and D) in one enterprise for which the ABR has registered that each firm has three employees in fte's (full time equivalent). In the Polisbus there is data on hours for firms A and B but not C and D, so this is a partial match. Because we have data on hours for six fte of the total of 12 fte that the enterprise employs, the partial match equals 50%. When the partial match is higher than 90%, we use the Polisbus data of A and B to infer labour hours data for the enterprise. In the example we would discard the enterprise from the analysis (the partial match being less than 90%). Labour hours for the remaining enterprises with partial matches are scaled by the estimated missing number of full-time equivalent employees.

In the majority of cases, the partial match indicates that labour hours data is missing for only a small percentage of the total enterprise employment.[13] We apply the scaling

[9] In the dataset used in this study (2006-2016), 95.5% of the enterprises consist of only one firm. The majority (77.2%) of the observations where an enterprise consists of multiple firms appear in the 2006-2009 subsample.
[10] The Statistics Netherlands labour employee data is split up into two data sets: Polisbus and Spolisbus. Slight differences have led to the name change. However, for our analysis these two datasets are perfectly compatible. Therefore, no further distinction between Spolisbus and Polisbus will be made. We will refer to the whole sample of Polisbus and Spolisbus data as the Polisbus data.
[11] The values in this section refer to the 2006-2015 sample unless explicitly stated otherwise.
[12] The majority (89%) of these partial matches take place in 2006-2009 (Polisbus data).
[13] For 25,269 partial observations the check indicates that no full-time equivalent employee is missing, implying that the missing firm(s) have a total employment that is less than 0.5 fte.

procedure for 32,895 enterprise observations.[14] We recode labour hours as missing for the remaining 16,554 enterprise observations for which the partial match was lower than 90% (i.e. indicating that labour hours data is unavailable for more than 10% of the total enterprise employment in fte's).

Table 3.1 shows the effects of matching the NFO database with the employee data. On average, 13.8% of the enterprises did not match at all and therefore do not have corresponding labour hours data.[15] After correcting for partial matches, we keep on average 85.5% of the enterprises.

**Table 3.1 Percentage of NFO enterprises for which we have Polisbus data**

| | 2006 | 2007 | 2008 | 2009 | 2010 | 2011 | 2012 | 2013 | 2014 | 2015 | 2016 | Mean |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Partial Match | 88.6 | 88.0 | 84.7 | 82.7 | 88.5 | 88.1 | 86.9 | 86.1 | 85.0 | 84.4 | 85.0 | 86.2 |
| Match with diff. < 10% | 86.8 | 85.6 | 83.4 | 81.4 | 88.4 | 88.1 | 86.9 | 86.0 | 85.0 | 84.4 | 85.0 | 85.5 |
| Full Match | 83.5 | 83.3 | 79.5 | 77.4 | 88.0 | 87.8 | 86.7 | 85.9 | 84.8 | 84.2 | 84.8 | 84.2 |

Note: Matched to an NFO enterprise does not automatically imply that this enterprise also has information on the other variables needed to estimate productivity. The firms included have to have a balance sheet total that is not missing to be included in this table. The values of 2016 are still under revision at the time of reporting.

From here onwards, we will refer to enterprises as firms to simplify terminology.

## 3.3 Variable construction

To estimate markups, a cost share and output elasticity are required. Therefore, a firm output variable (revenue or value added) and a free input variable are required. To calculate the output elasticity, a production function has to be estimated. In order to do so, a capital input and possibly a material or investment input variable are also required. We create proxies for all these variables with the available data (see
Table 3.2).

**Table 3.2 Variable Definitions**

| | |
|---|---|
| | **Output variable** |
| Revenues | Net sales minus returned goods, payed damages and discounts |
| Value added | Revenues − Production costs |
| | **Labour** |
| Labour hours | Number of payed working hours |
| Labour costs | Wages and social security contributions |
| Wage | Labour costs/ Labour hours |
| | **Capital** |
| Capital stock | Tangible fixed assets + Intangible assets – Depreciation |

[14] We divide total hours by a minimum scaling factor of 0.90. However, a large portion (35%) of the enterprises with a partial match had a scaling factor which was greater than 0.98 for whom only a small portion (less than 2%) of the total number of hours was missing.
[15] The match retains most (i.e. 90.9%) of the firms when we calculate TFP with labour costs instead of labour hours as input variable. For small firms the match obtains the greatest loss, as 9.9% of the firm observations are lost. While for large firms (>20 fte) the loss is minimal as only 2.8% of the firms observations do not have corresponding labour hours data.

| | |
|---|---|
| Tangible fixed assets | These are the physical assets intended for the sustainable support of a company's business operations (end of period and before depreciation). Examples: buildings, machines, installations, computers, transport equipment. |
| Intangible fixed assets | An identifiable non-monetary asset without physical form used for the production and delivery of goods or services, rental to third parties or for administrative purposes (end of period and before depreciation). Examples: licenses, patents, goodwill. |
| Depreciation | Accounting for impairment resulting from wear and tear (e.g. buildings, machinery, inventory), price drops (e.g. stocks) or other causes. In the dataset it is not possible to separate depreciation of tangible and intangible assets. |
| **Materials** | |
| Materials (i.e. Production costs) | This concerns the (raw) material consumption and the purchase value of the commodities and other operating expenses included in net sales. Other operating expenses include all costs, insofar as they do not relate to wages, depreciation and interest expenses. |
| **Investment** | |
| Investment | $\text{capital}_t - \text{capital}_{t-1} + \text{depreciation}_t$ |
| **Deflators** | |
| Deflator | The nominal values of the variables are deflated by the appropriate sector prices obtained from the input-output tables from the national accounts. We use the following variables to construct a deflator.<br>1. The capital deflator uses gross operating surplus ("Bruto investeringen in vaste activa; prijsindexcijfers").<br>2. The value added deflator uses gross value added in basic prices ("Bruto toegevoegde waarde basisprijzen").<br>3. The labour cost deflator uses wages ("Lonen") and employer social security contributions ("Sociale premies t.l.v. werkgevers").<br>4. The revenue deflator uses total ("Totaal").<br>5. The materials deflator uses consumption at purchasing prices ("Verbruik tegen aankoopprijzen").<br>The input-output table contains values in current prices and values in prices of last year. Therefore, by dividing the two we obtain the change in prices from one year to the next. We can then create a deflator for each input and output. All the inputs and outputs are in terms of 2010 prices. |

## 3.4 Missing observations

The NFO dataset contains on average 197,427 firms per year. After dropping sectors (2-digit NACE rev. 2) for which we could not calculate TFP or that had fewer than 100 firms per year[16], we were left with a sample of on average 180,044 firms per year. Our main results

[16] 10% or 5 % of 100 firms is 10 en 5 firms, which is too small a sample for Statistics Netherlands for reasons of anonymity.

are based on the non-financial business sector. For a complete list of the included sectors see appendix A.7.1.A.

Our data is unbalanced because different numbers of firms exit and enter every year.[17] TFP using labour hours as labour input variable can be calculated on average for 142,296 firms per year, while TFP using labour costs as labour input variable can be calculated for 156,494 firms per year. The total number of firms in our merged dataset is 400,737.[18] We discuss the main causes of missing observations.

With the ABR we can identify firms that appear in the ABR but not in the NFO ("NFO unobserved"). On average, 31,289 firms per year have no NFO data but are, according to the ABR, still operational. This may happen due to non-response (the majority of cases) or changes in the business characteristics of the firm. Most of these firms are small. On average 17.4% of the firm observations drop out of the NFO each year, which might have implications for our results in terms of sample selection. For the majority (65.5%) of the NFO firms in our merged dataset, the firm appears both in the ABR and NFO over the whole life cycle.

Nearly 94% of the NFO unobserved cases occur at the end or at the beginning of the sample period of the firm. In 60.9% of the NFO unobserved cases, the firm appears in the ABR before entering the NFO sample.[19] In 33.1% of the cases, the firm exits from the NFO sample to never reappear again while still appearing in the ABR.[20] Only in 6.0% of the NFO unobserved cases does the missing observation appear within the sample period. In most cases, a continuous sample of the firm can be followed within the NFO. The majority of the missing observations are firms appearing at a later time period in the NFO than the ABR, which is the least problematic as the firm is observed for an unbroken time period.

**Table 3.3 Missing observations in NFO**

| Years in ABR | Firm with missing data in NFO (%) | Data years missing in NFO (%) |
|---|---|---|
| 2 | 30.1 | 50.0 |
| 3 | 40.0 | 42.7 |
| 4 | 41.4 | 39.9 |
| 5 | 45.7 | 35.8 |
| 6 | 47.2 | 35.2 |
| 7 | 49.2 | 33.4 |
| 8 | 49.3 | 34.2 |
| 9 | 54.7 | 31.8 |
| 10 | 37.5 | 35.5 |

Table 3.3 shows an overview of the missing observations. Of the firms appearing on average nine years in the ABR, 54.7% are not included in the NFO for the full nine years. For these firms with missing observations, we miss on average 2.8 years of data of the firm (i.e. 31.8% of nine years). However, as previously stated, the majority of these missing observations

[17] See Olley and Pakes (1996) on the reasons why a balanced sample is not a good option when estimating TFP.
[18] There are 426,495 enterprises in the merged dataset. However 25,758 of these enterprises have no NFO data. This number refers only to the 2006-2015 sample.
[19] For example, the ABR contains small (self-employed) firms which do not enter the NFO as they do not pay corporate tax but income tax. Therefore, a small firm (self-employed) that grows and becomes a incorporated (NV or BV,), making the firm eligible to paying corporate tax, will cause the firm to enter the NFO dataset.
[20] In 22.2% of these cases, the enterprise dies in t+1 to t+3.

may be attributed to the firm appearing in the ABR before entering the NFO. Therefore, most of the missing observations are of the least problematic kind.

# 4 Methodology

## 4.1 The production function approach

This section first explains the production function approach to estimate markup as the ratio of the output elasticity and the cost share of the corresponding input. Next we discuss alternative methods to estimate the output elasticity.

The production function approach is developed by De Loecker and Warzynski (2012). The methodology is based on Hall (1988)who proposed that the industry specific markup can be uncovered from production data with information on inputs use and total revenue. The methodology was developed for firms for which the quantity of production is observed. However, most of the literature has used data in which the firms' production in quantities is not observed and instead (deflated) revenues are used. As a consequence, the estimate of the markup level is potentially biased and therefore should be interpreted with caution (De Loecker and Warzynski, 2012). Fortunately, the methodology is still informative about the changes in markup over time.

The production function approach is based on the assumption that firms minimize costs for inputs free of adjustment costs, so called free inputs. Therefore, at least one free input must be present in the production function. Generally, labour or intermediate inputs are used as free input. The markup is defined as the ratio between output price ($p_{it}$) over its marginal cost ($c_{it}$). The markup is derived from the first order condition of the firm's cost minimization problem with respect to the free input. This condition implies that the markup ($\mu_{it}$) equals the ratio between the output elasticity with respect to the free input $X$ ($\theta_{it}^{X}$), and the cost of the free input as a share of the firm's revenue ( $C_{it}^{X}/S_{it}$), or:

$$\mu_{it} = \frac{p_{it}}{c_{it}} = \theta_{it}^{X} \frac{S_{it}}{C_{it}^{X}}$$

Both the costs and the sales are directly observed in the data. However, two steps need to be taken to obtain the output elasticity. Firstly, a production function is estimated. Secondly, the partial derivative of the production function with respect to the free input is taken to obtain the output elasticity. Both steps are discussed below.

Estimating the production function comes with a host of considerations and choices. For example, the choice of the functional form, estimation procedure and proxy variable are all choices that need to be made. Unfortunately, these choices are not completely arbitrary and can lead to a different estimate of the TFP and output elasticity. After selecting the functional form and deciding on the other choices, the production function is estimated using semi-parametric techniques (see Wooldridge, 2009; Ackerberg et al., 2015). The next subsection elaborates on the estimation of different production functions.

In the second step, the production function is estimated. Taking the partial derivative of the production function with respect to the free input gives the output elasticity. Let us assume that intermediate inputs are the only free input in a Cobb-Douglas production function (lower case letters refer to logged values):

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it}$$

where output ($q_{it}$) is a function of capital ($k_{it}$), labour ($l_{it}$) and intermediate inputs ($m_{it}$). The partial derivative of this production function with respect to intermediate inputs gives the output elasticity $\beta_m$:

$$\theta_{it}^M = \frac{\partial lnQ_{it}}{\partial lnM_{it}} = \hat{\beta}_m$$

Therefore, in the case of the Cobb-Douglas production function, the output elasticity is constant for all firms, implying that the variation of the markup over time is solely driven by the cost share of the free input. A Cobb-Douglas production function leads to the same variation over time irrespective of the estimation method used to obtain the output elasticity.

In contrast, a Translog production function leads to a firm specific output elasticity and the resulting variation of the markup over time does not have to be equal over different estimation methods. The (second order) Translog production function is specified as:

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{mm} m_{it}^2 + \beta_{lm} l_{it} m_{it} + \beta_{kl} k_{it} l_{it} + \beta_{km} k_{it} m_{it} + \varepsilon_{it}$$

The output elasticity in the Translog case is derived as:

$$\theta_{it}^M = \frac{\partial lnQ_{it}}{\partial lnM_{it}} = \hat{\beta}_m + 2\hat{\beta}_{mm} m_{it} + \hat{\beta}_{lm} l_{it} + \hat{\beta}_{km} k_{it}$$

The output elasticity is therefore firm specific. The Translog specification takes into account that firms are likely to combine inputs in a different way to produce output.

## 4.2 Estimating the output elasticity

Three approaches are used to estimate output elasticities in the recent literature. The first approach is applied in De Loecker and Eeckhout (2018a) and Diez et al. (2018). Due to data constraints these authors use the cost of goods sold as free variable, which contains both material and labour inputs.[21] By summing materials and labour costs, it is assumed that material and labour are perfect substitutes. Taken to the extreme, this implies that a firm can keep sales constant by substituting all materials with labour expenses and vice versa. Also labour costs are assumed to be a free variable with no adjustment costs or other frictions that inhibit the input to adjust flexibly. This assumption is less likely to hold for many European countries, such as the Netherlands. If labour is, in fact, not a free input, the estimated output elasticity is incorrectly estimated. When we estimate the output

21 Diez et al. (2018) deviate from De Loecker and Eeckhout (2018a) methodologically as they estimate elasticities for each industry using the data of all the advanced economies over two separate periods (i.e. 1980-1998 and 1999-2016). De Loecker and Eeckhout (2018a) apply the estimated output elasticities obtained for the US to all countries.

elasticities separately for labour and materials with our data, the implied markups using labour are dramatically different from the markup obtained with materials: the levels are implausibly high and the time-series patterns are different.[22] If both materials and labour are truly free inputs, both should lead to identical markup patterns. The finding that this is not the case gives reason to believe that labour is not a free input in the Netherlands.

The second approach, applied in De Loecker and Warschynski (2012) and Weche and Wambach (2018), estimates a restricted profit production function. In a restricted profit production function materials inputs are subtracted from gross output giving value added as dependent variable. Therefore, only coefficients for labour and capital are estimated. This is problematic for the Netherlands for the same reasons as the first approach; labour cannot be used as a free input. Since the approach completely rests on the assumption that labour is a free input, it cannot be applied to the Netherlands.

The third approach, applied in Calligaris et al. (2018) and De Loecker et al. (2018b), estimates a gross output production function, implying that the output elasticity for labour and materials are estimated separately. Although this avoids the previously raised problems, the gross output production function has identification problems. Calligaris et al. (2018), Gandhi et al. (2017) and Ackerberg et al. (2015) clearly demonstrate that it is difficult to estimate this production function correctly. The main difficulty is in the identification of separate coefficients for materials and labour, as these two variables are often correlated.[23] A solution to the identification problem, applied in Doraszelski and Jaumandrue (2013) and De Loecker and Scott (2016), is to include wages a serial correlated input price that varies across producers- as an instrument. Calligaris et al. (2018) do not apply the needed correction and therefore report biased output elasticity estimates. Although this does not influence the within industry time trend, it does influence the between industry results in the Cobb-Douglas case.

This paper applies two main setups. These setups are chosen on the basis of comparability with recent studies and theoretical plausibility.

The first main setup applied in the paper is a gross output production function with wages included as an instrument and using labour hours as labour input. In contrast to the US, labour is not commonly viewed in the Netherlands as a flexible input that does not face any adjustment (i.e. hiring or firing) costs.[24] Therefore, we consider materials as the only free input variable for the identification of the relevant output elasticity.

The second main setup is similar to that of Loecker and Eeckhout (2017) and is chosen mainly for the reason of comparability. For this setup we add labour costs and material costs and assume that the aggregate is a free input. Then a production function is estimated

[22] The markups using labour leads to a weighted average markup increase of 133% over 2006-2016 and an average weighted markup level of 10.9.
[23] However, since labour is semi-fixed and intermediate inputs are flexible in the Netherlands, the problem of identification might already be mitigated.
[24] A distinction can be made between fixed and flexible contracts. Individuals with a flexible contract can be fired with relatively little adjustment cost, while individuals with a fixed contract come with considerable adjustment costs. Labour hours of employees with flexible contract could potentially be used to measure markups in the Netherlands.

where a single coefficient is estimated for the aggregate of labour and materials. This methodology avoids the potential identification problem of the first setup.

For each setup, we estimate two production functions. The Cobb-Douglas production function is easier to estimate and is often deemed more stable in the literature than the Translog production function, but is quite restrictive by imposing constant output elasticity.

Setup 1: Gross output (GO)

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \beta_m m_{it} + \varepsilon_{it}$$

Setup 2: De Loecker and Eeckhout (DLE)

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_{lm}(l_{it} + m_{it}) + \varepsilon_{it}$$

To avoid making the stringent assumption that the output elasticity is constant over time, the Cobb-Douglas production function can be estimated every year or over certain periods (See Diez et al., 2018; De Loecker and Eeckhout, 2017). When applied to our short sample, we find that the coefficients vary only slightly from year to year. However, this estimation is problematic when the number of observations within a sector becomes too small. Small sectors often display wider fluctuations in the estimated coefficients than large sectors. Therefore, this alternative should be applied with some caution, as yearly estimates might not be feasible for all sectors. Since this exercise does not lead to different results, it is not discussed in the results section.

We estimate the production function for large and small firms separately, to relax the assumption that the output elasticity is the same for different firm sizes. Given the large heterogeneity within a sector, it is not unconceivable that firms differ in their underlying production function. To test whether size influences firm production, we estimate separately the output elasticity for small firms ($\theta_{sm}$) and large firms ( $\theta_{lg}$). We define large firms as the 25% largest firms (in terms of output) and small firms as the remaining firms within a sector. The threshold was chosen at 25% to ensure sufficiently large subsamples.

# 5 Results

For both setups, we report results using the whole sample and the two subsamples (large and small firms). The results are robust over the different estimation choices within a setup. However, the results can differ between different setups. Therefore, a specification of each setup is chosen as base case: the Gross output setup with varying output elasticities over firm size (GO-S) is the base case in setup 1 and De Loecker and Eeckhout (DLE) as base case in setup 2. The GO-S is our preferred specification as it takes into account that large and small firms can produce differently and uses materials as free variable. The DLE specification is added for robustness and for comparison with other recent studies that use this approach (i.e. De Loecker and Eeckhout, 2017 De Loecker et al., 2018a and Diez et al., 2018). As the distinction between large and small firms in estimating the output elasticity makes almost no difference this setup and this distinction is not made in the recent literature, DLE is chosen as base case.

In this section, we discuss the following main results. First, we show the average weighted markup and different moments of the markup distribution and how they change over time. Second, our attention is turned to the sectoral heterogeneity, showing both the within and between differences in sectoral markups. Third, we decompose the markups into three elements: the cost ratio, output elasticity and revenue weights. Each element is analysed separately. Fourth, we show the relationship between markups and profit and revenue. Fifth, we conclude by analysing the markup of multinational firms. The sample is restricted to large multinational corporations to approach the dataset used in other papers.

## 5.1 Markups over Time

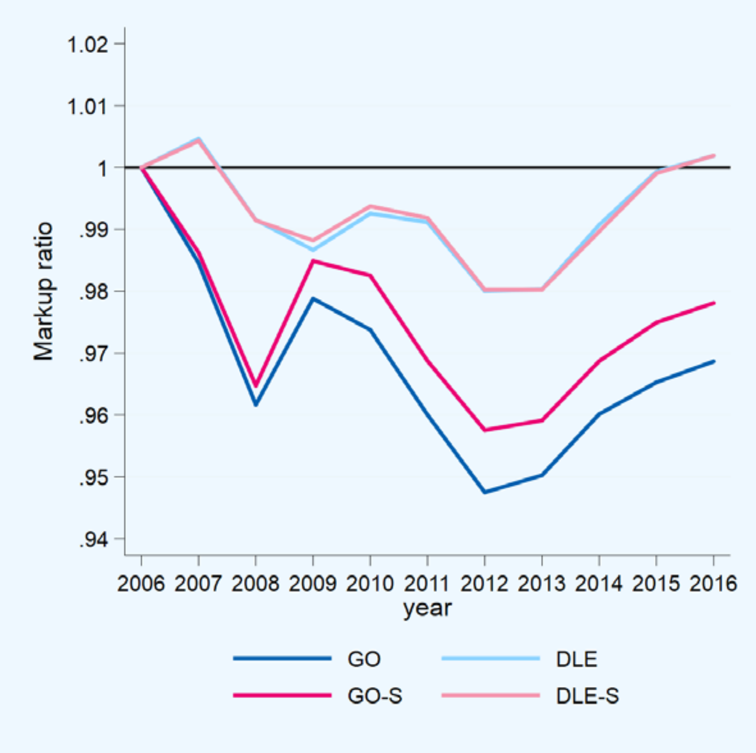
The main focus when discussing markups is on the changes over time of the (weighted) mean markup. The changes in markups over time are unbiased when using the production function approach.[25] Most studies report a sharp increase in the (weighted) mean markup in the US and Europe (including the Netherlands)(i.e De Loecker and Eeckhout, 2017, 2018; De Loecker et al., 2018a; Calligaris et al., 2018; Diez et al., 2018).

Figure 5.1 shows that both setups show no large increase in the weighted average markup in 2006-2016.[26] The preferred case GO-S shows a markup that has decreased over time. The markup initially decreases after 2006 then increases in 2009 to drop to its lowest level in 2012. After 2012 the markup starts increasing. However, by 2016 the markup is still 3% lower than that is it was in 2006.

[25] The levels of the GO-S and DLE markup have a relatively low correlation of 0.25, while the changes in the markups are more correlated (0.36). However, after deleting extreme markup values of 5 and greater, the markup levels of the GO-S and DLE still have a relatively low correlation (0.39) and the changes in the markups are highly correlated (0.86).
[26] Under the assumption that the output elasticities estimated for 2006-2015 are also applicable to the period before 2006, we can analyse the change in markups from 2000 onwards. Starting in 2000 leads to the same result as starting in 2006, that the revenue weighted markup is still not increasing over time for the different setups.

The trend of the DLE markup is a little different. The DLE markups first increases in 2007 and then decreases until 2009 after which it slightly increases and then drops to its lowest value in 2012. After 2012 the markup increases to a level that is just over the 2006 value in 2015. The DLE markup seems to move more pro-cyclical. The DLE markup seems less affected by the crisis as the mean markup is, at most, only 2% lower than the 2006 value. While the GO-S markup reaches a level that is over 4% lower than the 2006 value in 2012.

**Figure 5.1: Average weighted markups over time (2006 = 1)**




Note: This figure plots percentage changes in the average markup relative to the level in 2006. Hence the vertical axis represents the cumulative growth rate from the starting year.

Only in 2009 the GO setup shows an increase in the markup, while DLE setup shows a decrease in the markup. Labour explains this difference, which is slower to adjust than materials in the beginning of the crisis, leading to decreasing markups in the DLE case.

The result that markups are not increasing is in line with what Weche and Wambach (2018) find over a similar time period for other European countries. Also, De Loecker et al. (2018b) show that the weighted mean markup for Belgium does not rise after the early 2000s. Therefore, the results are in line with a growing body of evidence that the weighted mean markup in Europe has evolved differently than in the US.

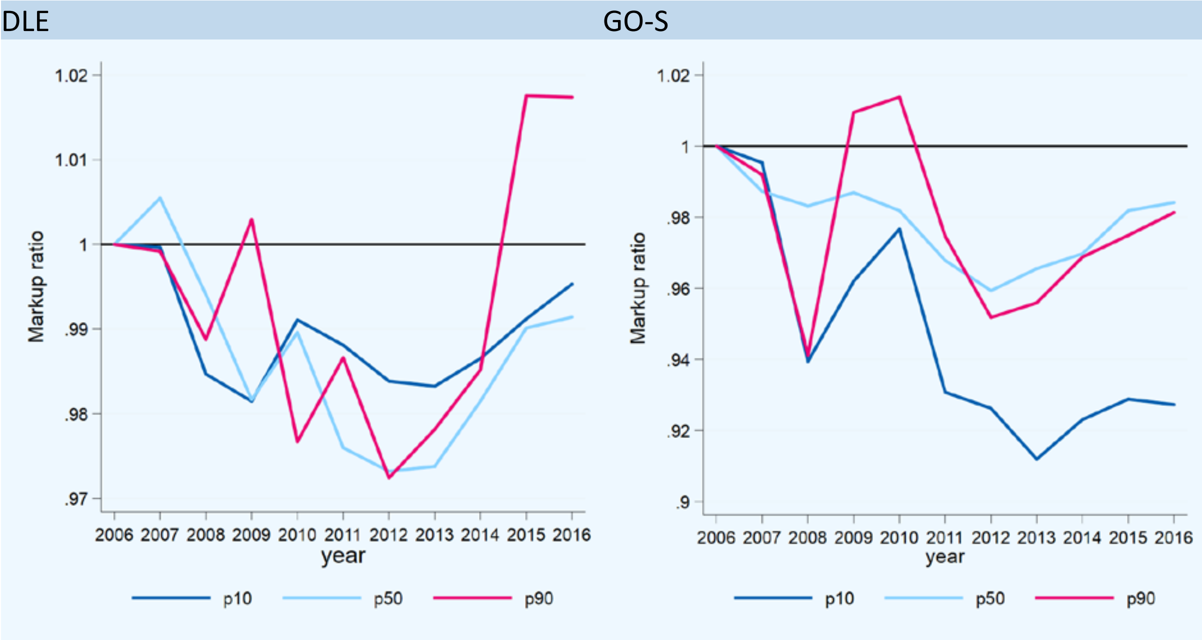
Figure 5.1 also shows that estimating the output elasticity over different size groups leads to a time trend that is similar to the case without separate estimation within the same setup. The fact that the elasticity is constant over time for each group and there is relatively little switching between size groups explains the similarity.

For the US, the median markup shows only a slight increase for publicly listed firms (See De Loecker and Eeckhout, 2017). The rise in the markups found in other papers for US and

Europe (including the Netherlands) is driven by firms that are located at the top decile of the weighted markup distribution (i.e. De Loecker and Eeckhout, 2017, 2018a; Diez et al., 2018).

The different moments of the weighted markup distribution give little indication of increasing markups in the Netherlands (See Figure 5.2). The top decile and median values approach the 2006 levels, while the bottom decile is falling behind. The top decile of the DLE markups shows the greatest increase in markups, while the rest has remained below the 2006 value. However, even in the DLE case, the markup increase of the top decile is slightly lower than a 2% increase over 11 years. Both GO-S and DLE show that the markups of the top decile initially increased at the start of the financial crises. Only during the second dip in 2012, the markup reached its lowest value. Since 2012 markups have been increasing for all moments, except the bottom decile in the GO-S case.

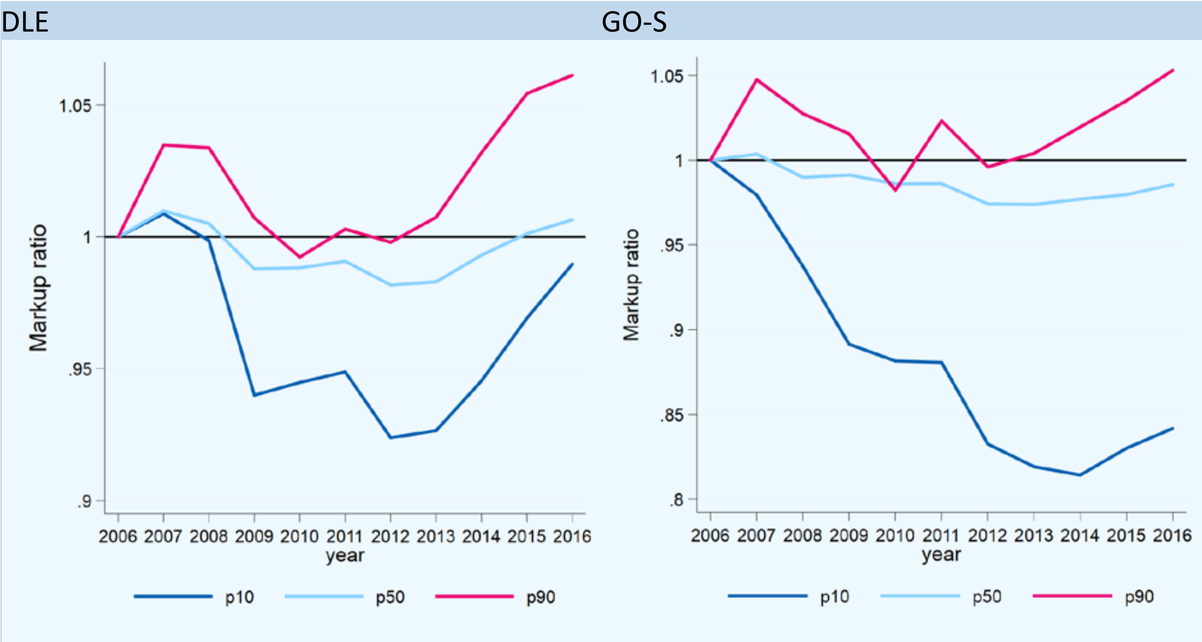
**Figure 5.2 Time path markup moments in the weighted distribution (2006 = 1)**




Note: This figure plots percentage changes in the moment of the distribution relative to the level in 2006. Hence, the vertical axis represents the cumulative growth rate from the starting year. Note that the composition of the different deciles changes per year (they do not consist of the same firms for each year) The markup distribution is weighted by revenue, implying that the markups of larger firms dominate the distribution.

The rise in the mean markup found in Calligaris et al. (2018) is driven by the top decile of unweighted markup distribution. Figure 5.3 shows the markup moments in the unweighted markup distribution for the Netherlands. Similar to Calligaris et al. (2018) the results for the unweighted markup distribution show the largest increase for the highest markup decile. However, the magnitude of the increase is relatively low (i.e. 6% and 5%). Calligaris et al. (2018) find that markups in the top decile increased by 25%. The markup increase in Calligaris et al. (2018) occurs after 2005, while the increase found in the top decile for the Netherlands starts in 2012. Compared to their results, the increase found in our sample is modest. Given that the top decile of the weighted distribution gives little to no indication of increasing markups and the unweighted distribution shows slightly increasing markups, we know that the largest firms do not increase their markups the most.

**Figure 5.3: Time path markup moments in the unweighted distribution (2006 = 1)**




Note: This figure plots percentage changes in the moment of the distribution relative to the level in 2006. Hence, the vertical axis represents the cumulative growth rate from the starting year. Note that the composition of the different deciles changes per year (they do not consist of the same firms for each year). The markup distribution is unweighted.

The levels are potentially biased when using the production function approach and should be interpreted with caution. Never the less, the differences and similarities between the markup approaches already become clear when looking at levels. In terms of the weighted mean markup the estimates are similar across the different setups (see Table 5.1).[27] The mean markup is estimated to be slightly higher than 1 and therefore seem plausible. The main difference between the GO setup and the DLE setup is the smaller standard deviation of the markup distribution in the latter case. When using the DLE setup markups of firms display less variation in markup levels, implying that firms charge relatively similar markup levels. The weighted average markup also increases and the standard deviation decreases when comparing the GO to the GO-S case. Therefore, estimating over different size groups (GO-S) leads to higher markup levels for large firms and less variation between firms. While for the DLE case the estimation over different size groups (DLE-S) does not lead to very different results.

**Table 5.1: Weighted average markup**

| Method | Mean (St. Dev.) |
|---|---|
| Setup 1 Gross output | |
| Gross output (GO) | 1.04 (0.82) |
| Gross output per size group (GO-S) | 1.07 (0.64) |
| Setup 2 De Loecker and Eeckhout | |
| De Loecker and Eeckhout (DLE) | 1.05 (0.23) |
| De Loecker and Eekhout per size group (DLE-S) | 1.03 (0.22) |

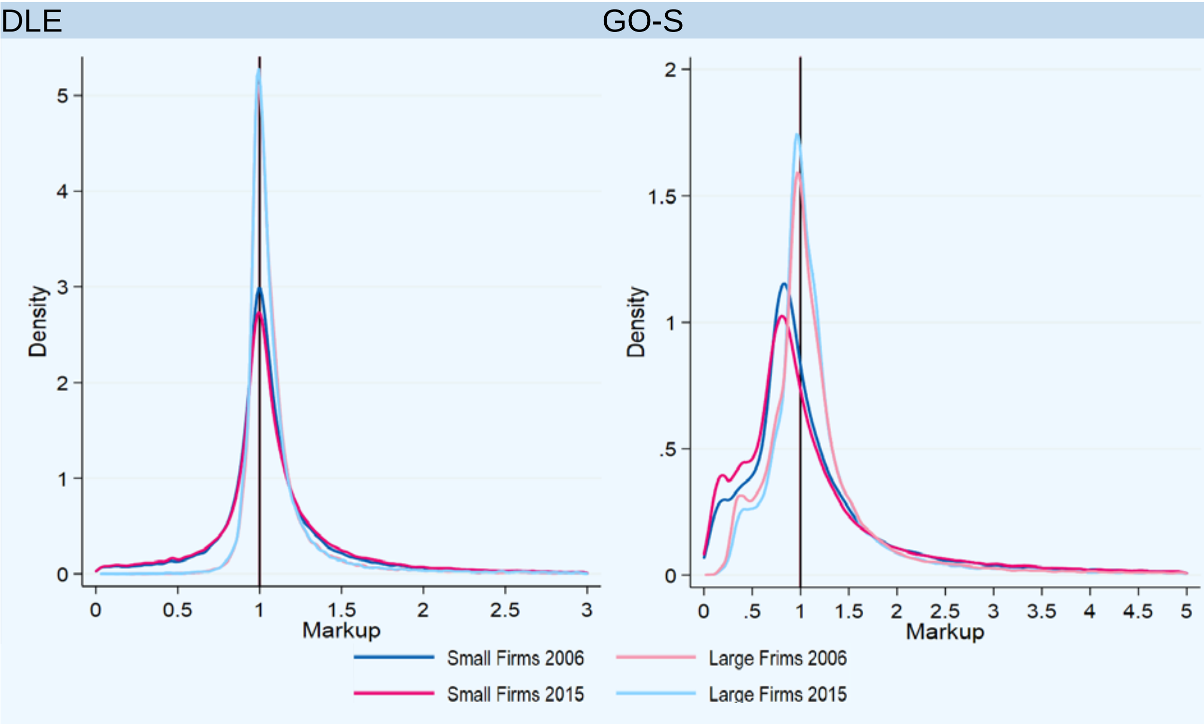
Note: The 1st and 99th percentile of the markup distribution has been truncated for each method. The markups are weighted with revenue. The markup mean is calculated as the mean of the weighted markup calculated for each year.

[27] In line with the recent literature, the values below the 1st and higher than 99th percentile of the markup distribution have been truncated for each method. This truncation is applied to all results shown in this section.

The difference in markup distribution between setups is clearly displayed in Figure 5.4. The DLE markups are highly concentrated around one and have little mass in the tails. This is especially true for large firms, defined as the top 25% firms in terms of revenue within an industry, that have a highly concentrated markup distribution, while smaller firms have more mass in the tails. The shape of the distirbution remains almost unchanged when comparing 2006 to 2015.

The GO-S markups are less concentrated and have more mass in the tails of the distribution. The distribution for large firms is still highly concentrated. However, in this case most large firms charge higher markups than smaller firms. Although the distributions change little over time. The distribution shifts slightly to the left, indicating that more firms are charging lower markups.

**Figure 5.4 The distribution of markups for small and large firms in 2006 and 2015**




Note: Large firms are defined as the 25% largest firms, in terms of revenue, within a sector; small firms are defined as the remaining 75%.

Calligaris et al. (2018) raise the question whether it is the same firm that charges high markups over time. To examine whether this is indeed the case the one-step transition matrixes for markups are examined. For the one-step transition matrix, the firms are ranked in terms of markups in year t and sector i and then divided into deciles. The same is done for the year t+1. The transition matrix shows how firms move across markup deciles from one year to the next. The differences in the distribution between setups also influence the transition matrix results. The more concentrated the distribution is, the smaller the ranges of the markup deciles are and changes in the markup are more likely to lead to switches in the deciles.

The transition matrices in Table 5.2 and Table 5.3 show that markups are volatile. The DLE markups are a lot more volatile than the GO-S markups. In fact, for GO-S, 77.4% of the firms remain in de same decile or move one decile higher or lower from one year to the next. Firms in the highest and lowest markup deciles are most likely to remain within the same decile, conditional on survival. The transition rates to deciles located far away from the decile a firm is located in are low, indicating stability.

The DLE transition matrix is more volatile as only 64.1% of the firms remain in the same decile or move one decile higher or lower from one year to the next. There is a high transition probability of more than 6% between the highest and the lowest markup decile. Also the exit rate for the highest markup decile is almost 2% higher for the DLE markups than the GO-S markups. The GO-S markups seem overall more stable than its DLE counterparts, indicating that high markup firms are more likley to remain a high markup firm in the GO-S than in the DLE case. The relative stability of the markup levels in the transition matrix adds another reason to prefer the GO-S over DLE results. In the GO-S case it can be said that it are often the same firms that charge high markups when going from one year to the next, while for DLE this is not the case.

**Table 5.2: Transition matrix DLE markups (sample averages)**

| | | t+1 | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | Exit |
| | D1 | 58,0 | 16,9 | 5,6 | 3,2 | 2,1 | 1,7 | 1,5 | 1,8 | 3,2 | 6,1 | 18,8 |
| | D2 | 14,3 | 38,1 | 18,9 | 8,3 | 4,7 | 3,0 | 2,4 | 2,6 | 3,8 | 3,9 | 10,0 |
| | D3 | 4,9 | 16,9 | 29,3 | 18,3 | 9,5 | 5,5 | 4,0 | 3,8 | 4,3 | 3,4 | 8,6 |
| | D4 | 2,8 | 7,3 | 16,7 | 25,4 | 17,7 | 10,0 | 6,3 | 5,4 | 5,3 | 3,1 | 8,3 |
| t | D5 | 2,0 | 4,1 | 8,4 | 16,3 | 24,2 | 17,6 | 10,3 | 7,7 | 6,3 | 3,0 | 8,2 |
| | D6 | 1,6 | 2,7 | 5,1 | 9,0 | 16,5 | 25,0 | 18,2 | 11,1 | 7,7 | 3,1 | 8,5 |
| | D7 | 1,5 | 2,2 | 3,7 | 5,8 | 9,4 | 17,0 | 27,9 | 18,6 | 10,1 | 3,7 | 9,5 |
| | D8 | 2,1 | 2,6 | 3,8 | 5,3 | 7,3 | 10,7 | 17,5 | 28,0 | 16,8 | 6,0 | 12,4 |
| | D9 | 3,6 | 3,9 | 4,4 | 5,3 | 6,3 | 7,3 | 9,3 | 15,7 | 29,3 | 14,9 | 16,1 |
| | D10 | 6,7 | 4,3 | 3,6 | 3,2 | 3,2 | 3,1 | 3,5 | 5,6 | 15,0 | 51,9 | 30,8 |

Note: For the transition matrix the firms are ranked in terms of DLE markups in year t and sector i and then divided into deciles. The same is done for the year t+1. The transition matrix shows how firms move over markup deciles, when going from one year to the next. D10 is the decile with the highest markups and D1 is the decile with the lowest markup. The transition probabilities are the average one-step transition rates over all years. The Exit rate indicates the percentage of firms that exit the sample when going from year t to year t+1.

**Table 5.3: Transition matrix GO-S markups**

| | | t+1 | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | D1 | D2 | D3 | D4 | D5 | D6 | D7 | D8 | D9 | D10 | Exit |
| t | D1 | 68,8 | 16,0 | 4,4 | 2,5 | 1,7 | 1,4 | 1,2 | 1,1 | 1,0 | 2,0 | 17,1 |
| | D2 | 15,1 | 49,8 | 18,1 | 6,1 | 3,2 | 2,1 | 1,6 | 1,3 | 1,1 | 1,6 | 10,8 |
| | D3 | 4,0 | 17,9 | 42,4 | 18,3 | 6,7 | 3,8 | 2,5 | 1,6 | 1,3 | 1,4 | 9,3 |
| | D4 | 2,3 | 6,1 | 18,6 | 38,2 | 17,8 | 7,1 | 3,9 | 2,7 | 1,7 | 1,6 | 9,3 |
| | D5 | 1,7 | 3,2 | 6,9 | 18,6 | 37,3 | 17,2 | 7,0 | 3,9 | 2,5 | 1,8 | 9,3 |
| | D6 | 1,4 | 2,0 | 3,9 | 7,2 | 18,2 | 37,4 | 16,8 | 6,6 | 4,1 | 2,4 | 9,9 |
| | D7 | 1,2 | 1,5 | 2,5 | 4,1 | 7,3 | 18,0 | 38,1 | 17,1 | 6,7 | 3,6 | 10,7 |
| | D8 | 1,1 | 1,2 | 1,6 | 2,8 | 4,2 | 7,2 | 18,6 | 40,7 | 16,7 | 6,0 | 11,9 |
| | D9 | 1,1 | 1,1 | 1,2 | 1,6 | 2,6 | 4,5 | 7,3 | 18,8 | 46,2 | 15,6 | 15,4 |
| | D10 | 2,0 | 1,7 | 1,4 | 1,6 | 1,8 | 2,5 | 4,0 | 7,1 | 19,3 | 58,6 | 31,1 |

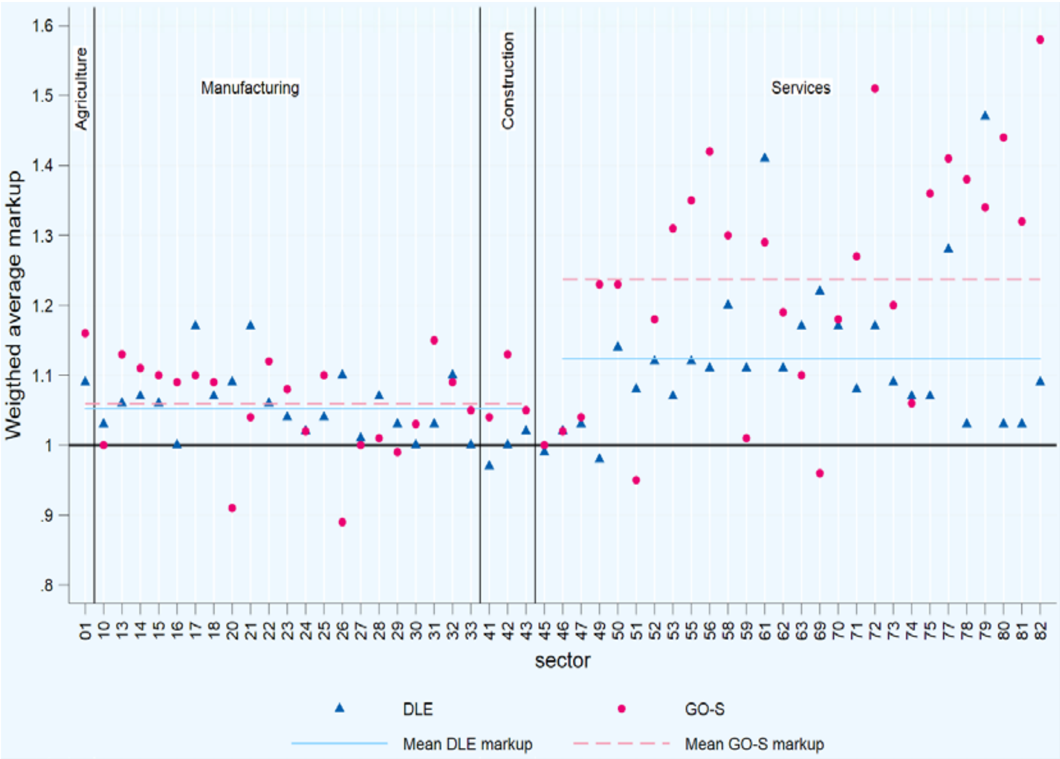
Note: For the transition matrix the firms are ranked in terms of GO-S markups in year t and sector i and then divided into deciles. The same is done for the year t+1. The transition matrix shows how firms move over markup deciles, when going from one year to the next. D10 is the decile with the highest markups and D1 is the decile with the lowest markup. The transition probabilities are the average one-step transition rates over all years. The Exit rate indicates the percentage of firms that exit the sample when going from year t to year t+1.

## 5.2 Markups over sectors

The aggregate results often hide a rather large degree of heterogeneity. Analysing markups at the sector level helps unravel this picture. Figure 5.5 shows that the markup levels differ greatly between sectors. In most cases, the estimated sector markup levels also differ across the setups. The largest difference is obtained for sector 82 (Office administrative, office support and other business support activities) where the GO-S markup level is 1.58, while DLE markup is 1.09. Despite the differences, both the GO-S and DLE indicate that the average markup for service sectors is often higher than that of the other sectors. However, the difference between the service and other sectors is larger for GO-S.

The differences between the markup levels of GO-S and DLE are smaller for nonservice sectors (1.8 percentage point on average) than the service sectors (8.4 percentage points). The presence of more small firms may increase the difficulty of estimating the markup level for many service sectors. The service sectors are often more labour intensive and this leads to a larger wedge between the setups. Considering that labour is not a free variable the wedge indicates that the DLE markup results are more problematic for the service industry than the manufacturing sector.

**Figure 5.5: Weighted average markup across sectors**

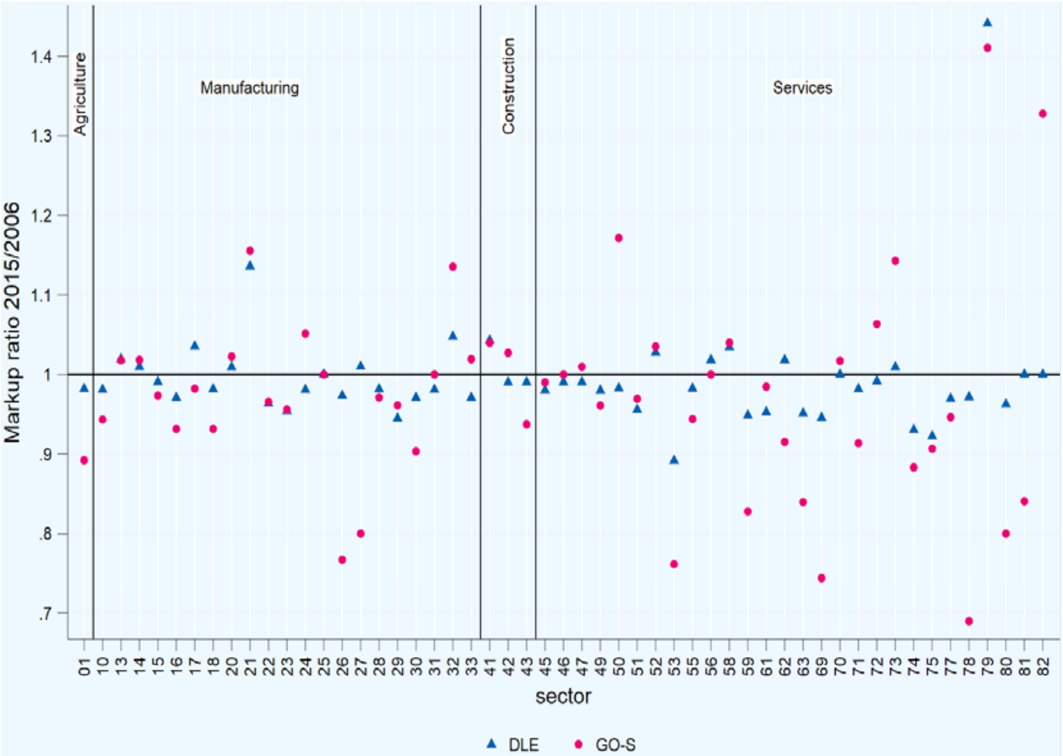



Note: This figure shows the revenue weighted markup for each 2-digit sector for both DLE and GO-S. The mean markup is displayed seperately for non-service sectors (sectors 1-43) and service sectors (Sector 45-82). See appendix A.2 for definition of sector codes.

The production function approach may affect the estimated levels of the markup. However, if both setups estimate markups correctly then the changes over time should be unaffected and similar. In 77.3% of the sectors, the DLE and GO-S give the same indication of whether the markup is rising or falling. In most cases, the markup cumulative growth rate is small, as the ratio is close to one (Figure 5.6). However, it is clear that choosing for DLE or GO-S matters for the magnitude of time trend. The average within sector difference between the setups is 6.7 percentage points of cumulative growth rate. The differences in cumulative growth rate between GO-S and DLE are twice as large for the service sector (9.0 percentage points) than the other sectors (4.5 percentage points).

For the average sector, the markup is decreasing over time. The markup decrease is larger when using GO-S (2.8%) than DLE (0.5%). Both the DLE and GO-S markup ratios are frequently lower for the service sector, indicating that some service sectors have experienced large declines in markup.

**Figure 5.6: Markup ratio 2015/2006**



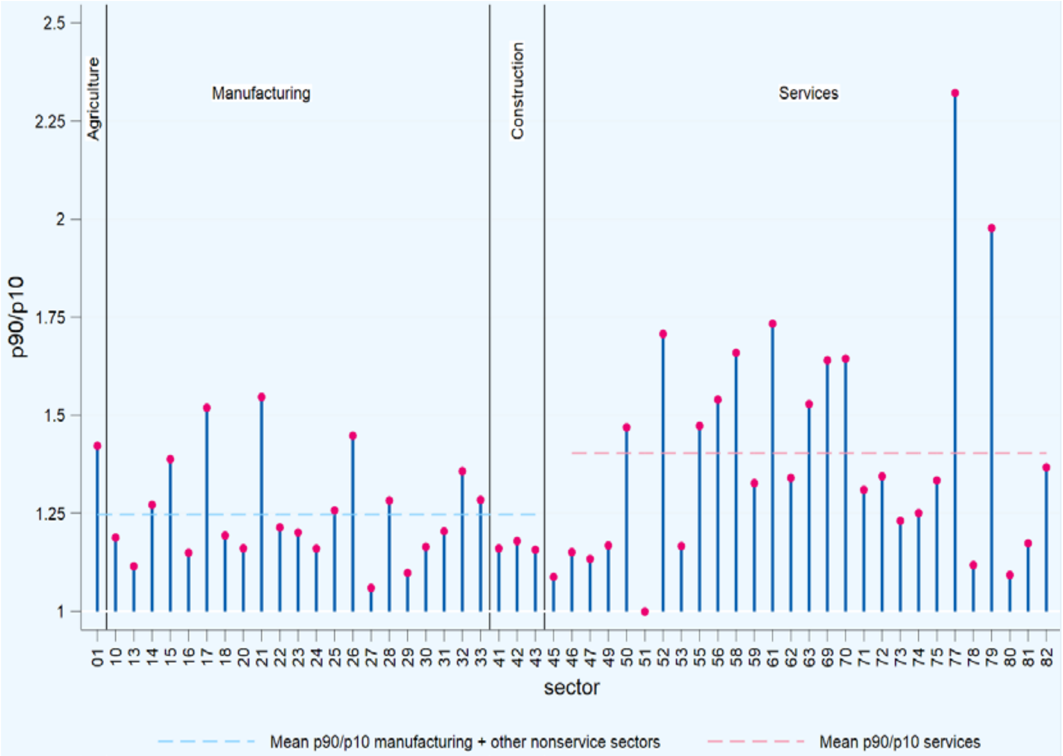

Note: This figure plots the ratio between the 2015 and 2006 weighted markup level for each sector. Hence, the vertical axis indicates the cumulative growth rate from 2006. For example the value 1.1 indicates that the weighted average markup in 2015 is 10% higher than in 2006.

To illustrate the heterogeneity within a sector, we present in Figure 5.7 and Figure 5.8 the p90/p10 ratios for DLE and GO-S revenue weighted markup distribution. A higher ratio indicates larger within sector differences. For DLE markups and the median sector, the firm located on the 90th percentile has a markup that is around 24% higher than the firm located on the 10th percentile. For GO-S markups and the median sector, the spread increases; firms located on the 90th percentile have a markup that is around 81% higher than firms located on the 10th percentile.

The markup distribution is revenue weighted, which means that the markups of larger firms are assigned a larger share of the distribution. This implies that if the sector is dominated by large firms that charge a similar price, the within sector spread will be low. For example, sector 51 (air transport sector) is dominated by one firm. Therefore, the p90/p10 ratio is 1. If the distribution would not be weighted, a greater spread is attained in most cases.

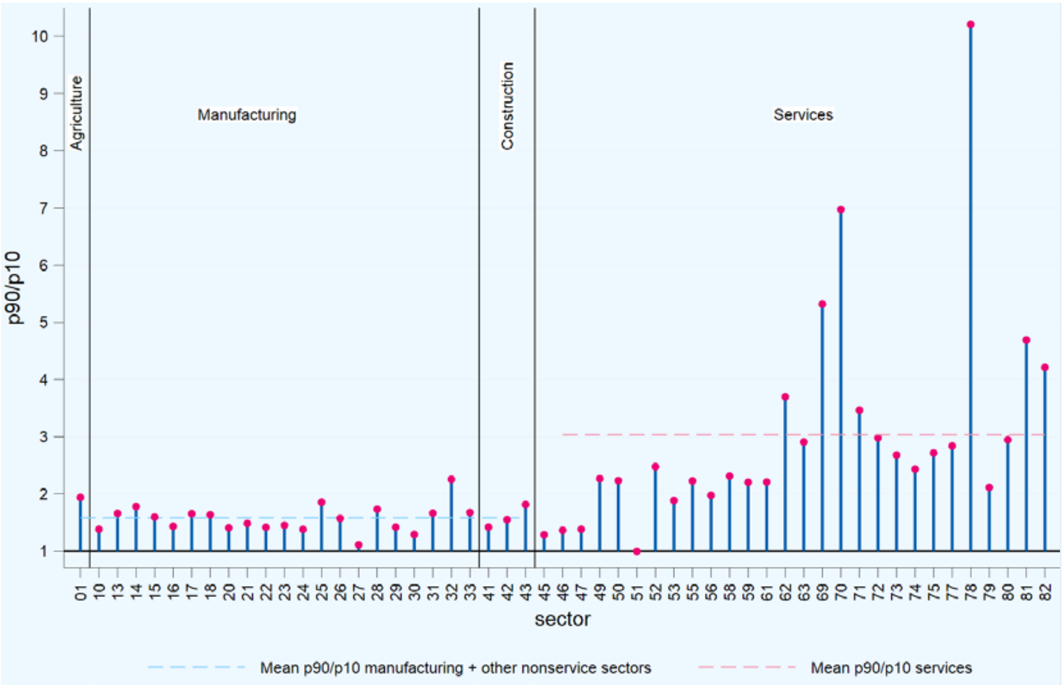
The average spread is higher in the service sector than the manufacturing sector. However, even within the manufacturing and service sector there is a lot of heterogeneity. The differences between the manufacturing and the service sector are greater for GO-S markups. Also, the GO-S markups frequently display more within sector heterogeneity than the DLE markups. For example, in sector 70 (activities of head offices; management consultancy activities) the firm on the 90th percentile charges a markup almost 1.6 times higher than the firm located on the 10th percentile when using DLE markups. For GO-S markups, the firm on the 90th percentile charges a markup 6.6 times higher than the firm located on the 10th percentile.

### Figure 5.7: Within sector p90/p10 ratio of DLE markups in 2015




Note: This figure plots the ratio ninetieth percentile and the tenth percentile for the weighted markup distribution of each sector in 2015. Hence, the vertical axis indicates how much higher the markups are for the ninetieth percentile when compared to the tenth percentile. For example, the value 1.5 indicates that the markup of the ninetieth percentile is 50% higher than that of the tenth percentile.

### Figure 5.8: Within sector p90/p10 ratio of GO-S markups in 2015




Note: This figure plots the ratio ninetieth percentile and the tenth percentile for the weighted markup distribution of each sector in 2015. Hence, the vertical axis indicates how much higher the markups are for the ninetieth percentile when compared to the tenth percentile. For example, the value 1.5 indicates that the markup of the ninetieth percentile is 50% higher than that of the tenth percentile.

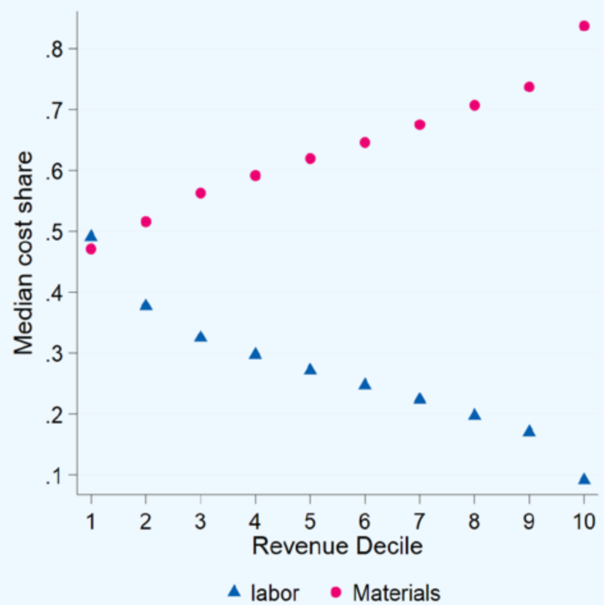
## 5.3 Untangling markups

The average weighted markup consists of three components: the cost share, the output elasticity and the revenue weight. This section will disentangle the components to understand the differences between DLE and GO-S and check if there are components that point to increasing markups.

### 5.3.1 Cost share

The first component is the cost share. Figure 5.9 provides the median cost share per revenue decile. It shows that firms with higher revenues per sector have lower labour cost shares. The revenue deciles are created by ranking the firms by revenue in year t and sector i and then dividing them into deciles. Firms located in the highest revenue decile of a sector have an average labour share that is five times smaller than firms located in the lowest revenue decile. For materials the reverse is true, as larger firms have higher material cost shares than smaller firms. When the median labour and material cost share are summed per revenue decile, the average value is 0.90 with a low standard deviation of 0.02. This indicates that the large difference in cost shares between large and small firms disappears when considering a composite input. This explains why the estimation over different sizes (DLE-S) does not lead to different output elasticities and markup levels in the DLE case. The finding that the cost share of labour and materials differ over firm size has implications for the estimation of markups and the difference between large and small firms in terms of markup levels.

**Figure 5.9: The median cost share per revenue decile**

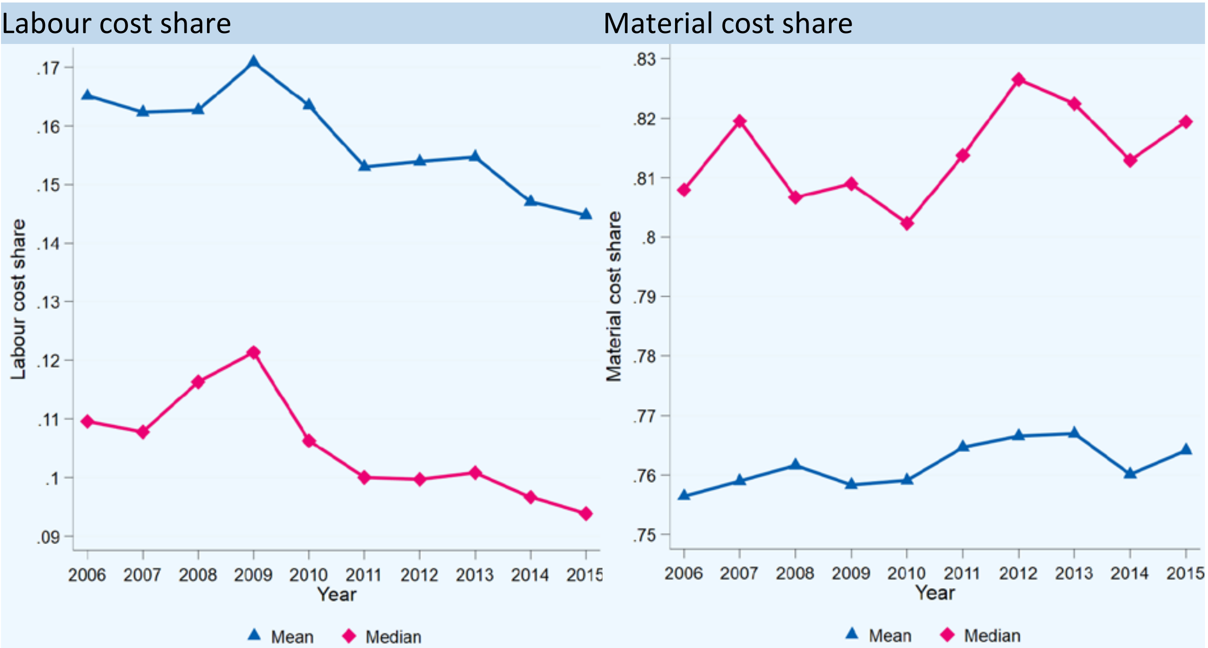



Note: The respective labour (material) cost share is defined as labour (material) costs divided by revenue.

Figure 5.10 (left) shows how the revenue weighted labour cost share slightly declines over time. Both the mean and median labour cost share decline by slightly less than 2% over time, whereas the material cost share remains more stable and only increases at most by 1%. This indicates that for large firms the labour cost share declines and the material cost share slightly increases over time. As weighted cost shares are relatively stable over time, they are unlikely to contribute to large changes in the average weighted markup. In our case, only the material input should be considered a free variable. Choosing a free variable containing or consisting of labour will lead to incorrect results, as both the time trend and composition over size differs.

Figure 5.10 (left) also shows that the labour share peaks in 2009, which may indicate labour hoarding at the beginning of the crisis. This could be the reason why GO-S and DLE average markups show different movements in 2009: the material cost share remains constant, while the labour costs share increases. If the slow adjustment of labour costs is due to the fact that labour is not a free variable, the assumption of the DLE setup is violated and the markup estimation is biased. However, if labour costs can be freely adjusted but firms choose to keep their labour, then it is a firm choice and should lead to lower markups as revenue declines.

**Figure 5.10: The (revenue weighted) cost shares over time**




Note:The median is the median value of the revenue weighted distribution. While the mean is the revenue weighted mean.

## 5.3.2 Output elasticity

The second component is the output elasticity. The output elasticity is assumed constant over time and therefore cannot contribute to an increase in the weighted average markup. By estimating the output elasticity separately for small and large firms[28], we introduce some heterogeneity. The large firms are defined as the 25% largest firms (in terms of revenue) within a sector. Small firms are defined as the remaining 75%. The threshold was chosen at 25% to ensure sufficiently large subsamples. The firms that switch between size groups could influence the trend over time, however this effect is small as the output elasticity is kept constant within the two size groups.

[28] The yearly estimation of the output elasticities will not be discussed. Although they lead to similar results, the estimations are unstable for the small sectors. Therefore, in future work the estimation of the output elasticity will be made across bins of 5 years to ensure the presence of sufficient observations. For the larger sectors the parameters hardly change when estimated yearly.

The estimation shows that for the Gross output setup, estimating the production functions separately leads to large differences in the estimated output elasticity ($\beta_M$). Large and small firms seem to produce differently. Large firms use more material and less labour inputs into production. Therefore, the output elasticity of materials of large firms is significantly higher than that of small firms. The resulting elasticity for large firms is 0.67 while it is 0.55 for small firms. This implies that when the jointly estimated output elasticity is applied, the markup level of small (large) firms will be over (under)estimated. The assumption that large and small firms produce similarly does not hold. This is the reason why the GO-S markups are chosen as the base case for the gross output setup.

In the DLE case where labour and material costs are combined, the estimated output elasticity does not change when estimated separately for large and small firms. The logic behind this is that the combined costs are relatively similar for firms of different sizes. As a consequence, the estimated output elasticities do not differ much over firm size. The DLE approach assumes substitutability of labour and materials. However, materials and labour cannot easily be substituted in many cases. In fact, the substitutability of labour for materials might depend on other factors, such as firm size.

**Table 5.4: Average output elasticity over sectors**

| Setup | Firm Size | $\beta_L$ | | $\beta_M$ | |
|---|---|---|---|---|---|
| | | Mean (St. Dev.) | Median | Mean (St. Dev.) | Median |
| GO | All | 0.28 (0.10) | 0.27 | 0.63 (0.12) | 0.64 |
| GO-S | Small | 0.31 (0.09) | 0.30 | 0.55 (0.15) | 0.59 |
| | Large | 0.19 (0.08) | 0.16 | 0.67 (0.14) | 0.70 |
| | | | | $\beta_{LM}$ | |
| DLE | All | | | 0.94 (0.03) | 0.95 |
| DLE-S | Small | | | 0.92 (0.05) | 0.93 |
| | Large | | | 0.92 (0.05) | 0.93 |

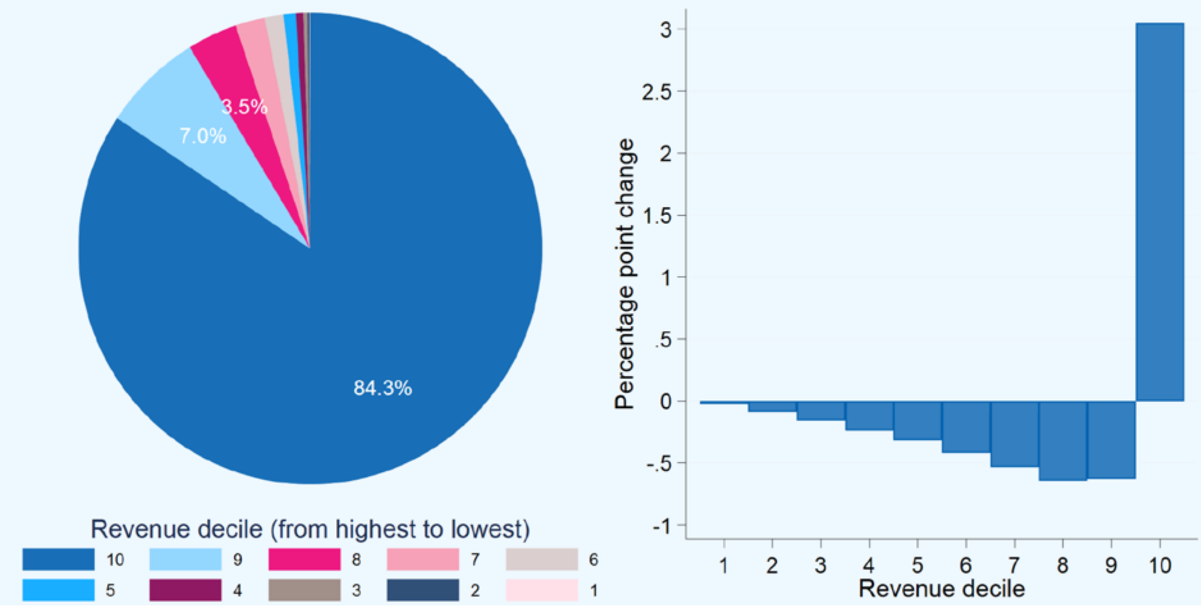
Note: The regressions for small (large) firms are restricted to firms that are small (large) in year t and t-1. This leads to sample differences for the estimation for the whole sample and explains why the estimation DLE-S for small and large firms are both slightly below the estimated value for the whole sample (DLE).

### 5.3.3 Revenue weights

The third component is that of revenue weights. Figure 5.11 shows that firms belonging to the 10% highest revenue firms within a sector account for the majority (84.3%) of the total revenue. The second and third highest revenue decile firms account for 7.0% and 3.5% of total output, respectively. The importance of the remaining deciles is very small with a remaining share of 5.2% of total output. This figure clearly demonstrates that the largest firms dominate the output within a sector. Interestingly, the share of the top revenue decile is the only share that has increased over time, by 3%. Other revenue deciles face a lower market share. The change in revenue weights is too small to result in large changes in markups. However, the importance of the largest revenue group, which is slightly increasing over time, indicates that the average weighted markup is dominated by relatively few firms.

**Figure 5.11: Revenue weights**

| Percentage of total revenue contributed by revenue decile in 2015 | Change in the percentage of total output contributed by revenue decile between 2006 and 2015 |
|---|---|



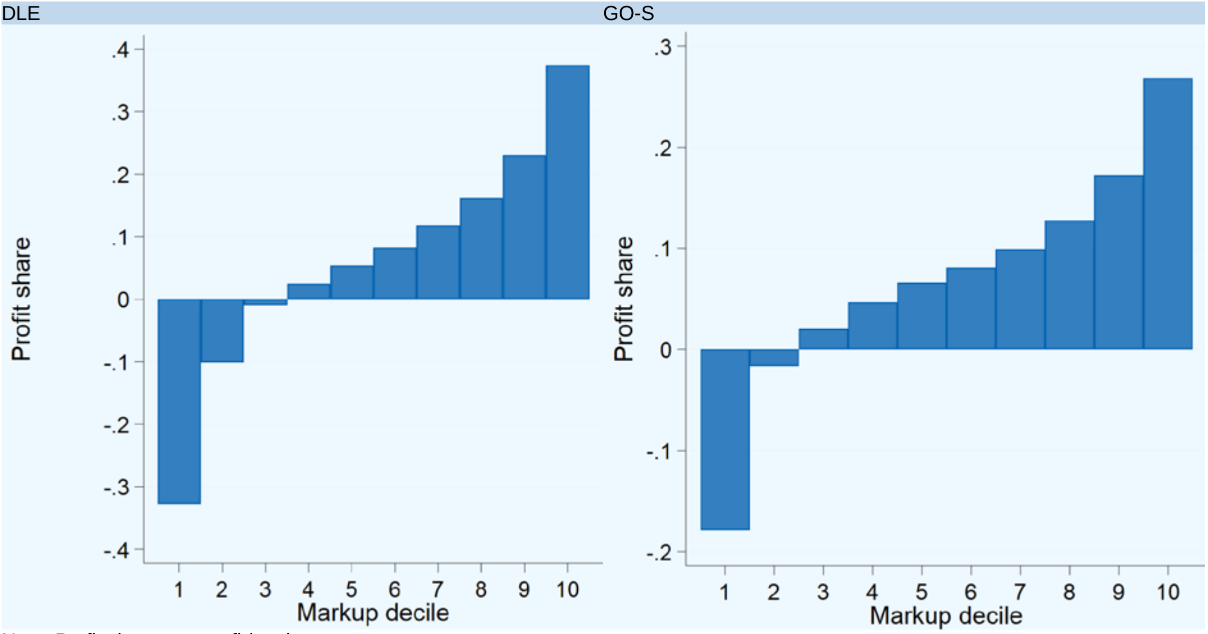

Notes: The revenu decile are created for each sector year. Therefore the highest revenue decile contain all the firms beloning to the highest revenue decile of their sector.

In sum, all three of the markup components do not give any indication of a change that could lead to a strong markup increase in our data.

## 5.4 Profit

High markups do not necessarily indicate higher profit rates. When a firm incurs higher fixed costs, the markup will rise to recover the fixed cost. Figure 5.12 shows, however, that firms with higher markups also have higher profit rates.

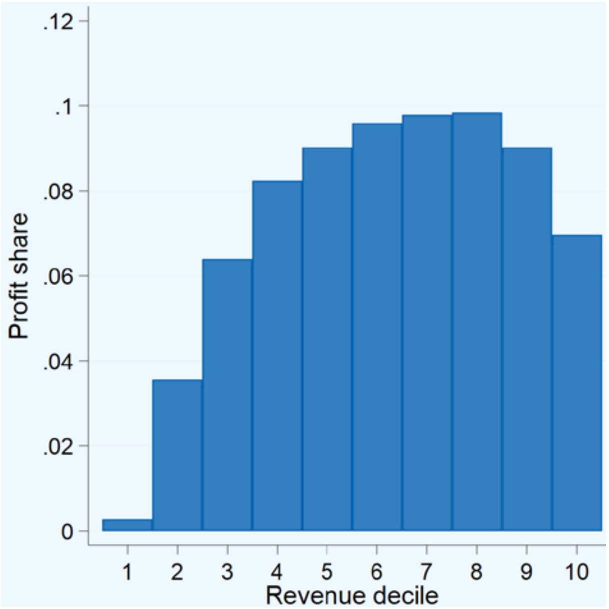
Figure 5.12: Profit rate per markup decile in 2015




Note: Profit share=net profit/total revenue.

The relationship between firm size and profit is less straightforward (Figure 5.13). Firms in revenue decile 7 and 8 have the highest profit rate. However, the differences in the average profit rate are quite small over the middle deciles. All the results are robust to taking the median profit rate instead of the mean.

Figure 5.13: Profit rate per revenue decile in 2015




## 5.5 Multinational markups

Can we explain the difference between our result and that of De Loecker and Eeckhout (2018a)? De Loecker and Eeckhout (2018a) and Diez et al. (2018) base their markup results on the Worldscope dataset, which contains standardized financial statements for over 70,000 companies worldwide. Data coverage starts in 1980 and spans 134 countries. The individual companies tend to be large and consist mainly of publicly traded, mostly multinationals, though there are also privately held firms. De Loecker and Eeckhout (2018a) and De Loecker et al. (2018b) flag their concern about the representativeness of the sample.

To approach the Dutch sample of the Worldscope dataset, a sample of firms with foreign affiliates (multinationals) that belong to the highest revenue decile of a sector are selected. This leaves us with a sample of around 2900 firms per year that span all sectors. This is significantly larger than the Dutch sample in Worldscope but contains similar firms (i.e. very large multinational corporations).

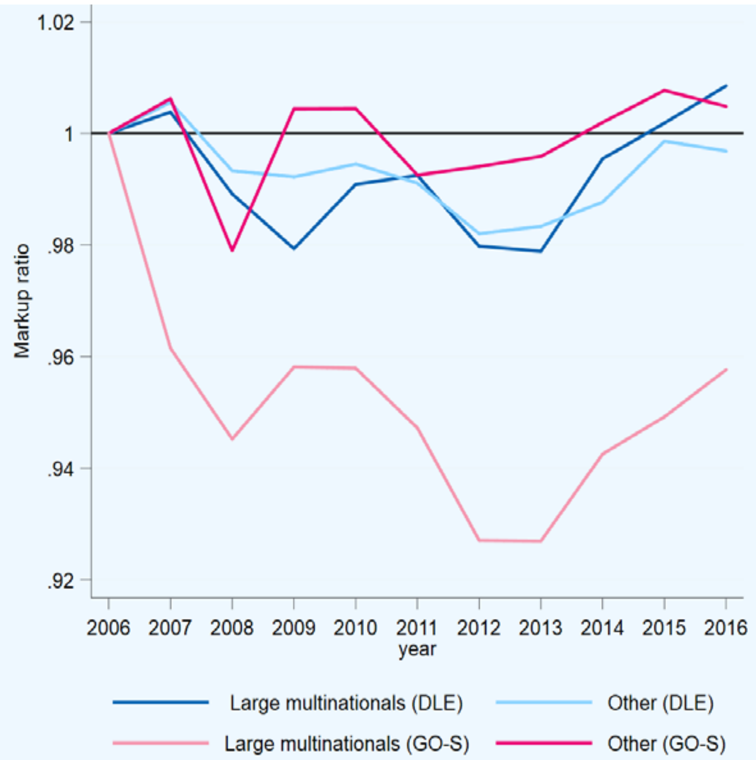
There are no clear differences between the markup levels charged by large multinationals and that of other firms, as the weighted mean markup is similar or lower (see Table 5.5).

**Table 5.5 Weighted average markup large multinationals**

| | Large multinational | Other |
|---|---|---|
| DLE | 1.05 (0.17) | 1.06 (0.29) |
| GO-S | 1.01 (0.37) | 1.12 (0.84) |

Although there are various issues with estimating the markup levels, the changes over time are relatively insensitive for these measurement issues and should more or less reflect actual changes in markups. In our sample, the weighted mean markup of large multinationals increases by 1% in the DLE case and decreases by 4% in de GO-S case relative to the 2006 value (see Table 5.5), leading us to conclude that large Dutch multinationals do not show a large increase in their markups.

**Figure 5.14: Time path of the weighted average markup for large multinationals**




Note: Large multinationals are firms that have at least 1 branch located in another country than the Netherlands and are located in the top revenue decile of a sector

The fact that our findings differ from those of De Loecker and Eeckhout (2018a) raises the question why. There are, at least, two possible reasons, explained below in sections 5.5.1 and 5.5.2.

### 5.5.1 Sample differences

Sample differences might drive the results. The results of De Loecker and Eeckhout (2018a) only apply to a small sample of large publicly listed firms in the Netherlands. Diez et al. (2018) also use the Worldscope data and indicate that they have 4,336 observations over 36 years, therefore around 120 firms per year. Worldscope covers the financial sector, which is not included in our sample. However, the costs of goods sold are missing for nearly all firms in the financial sector making it impossible to calculate markups of these firms. Therefore, this sector cannot drive the difference between our results and that of papers using the Worldscope data. De Loecker and Eeckhout (2018a) find that markups for the Netherlands have only risen since the last two years of the data. For the interpretation of the De Loecker and Eeckhout (2018a) result, we should check what is driving this result.

To check which firms drive the markups estimated on Worldscope data, we have studied in detail these data. Thomson Reuters datastream has a number of predefined constituent lists. WSCOPENL is a list of Dutch companies that are covered by the Worldscope company accounts database, which is the sample used. The data from 2000 till 2015 is used because this timeframe corresponds with our analysis. There are on average 176 firms per year in the data for which markups can be calculated. The number of firms drops from 199 firms in 2000 to 129 in 2015. There are 320 firms for which we can calculate markups for one of more years. The average firm only appears for 8 years in the data. There are 64 firms for which we can calculate a markup for each year.

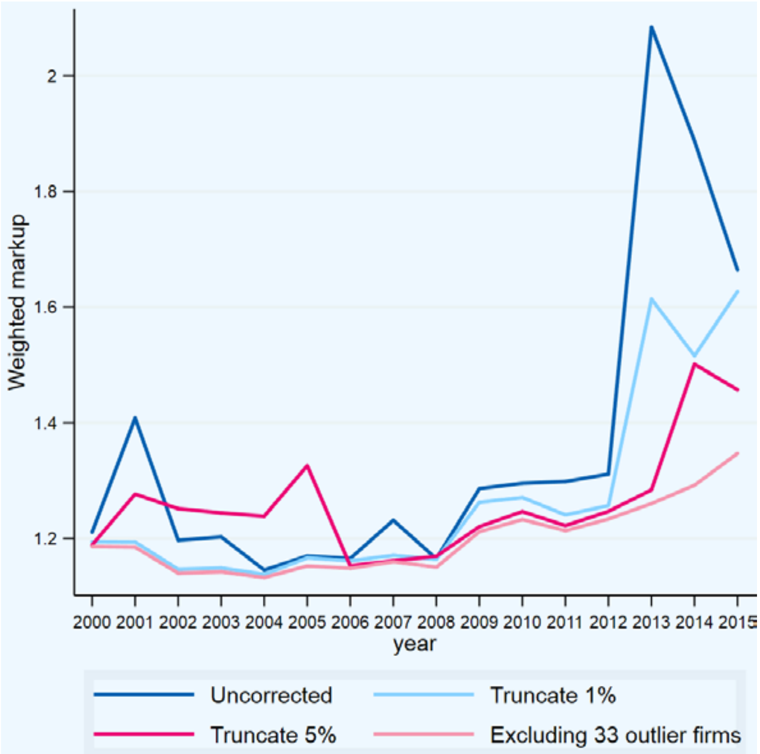
The output elasticities reported in the appendix of De Loecker et al. (2018a) are used for the markup analysis. These output elasticities are calculated for American public listed firms and are likely similar to the output elasticities that are applied in De Loecker and Eeckhout (2018a) for the Netherlands.

The uncorrected average weighted markup shows a sharp rise in 2013 (see Figure 5.15). This rise is driven by observations that are outliers. Figure 5.15 shows the impact of three different outlier strategies. Two relatively standard outlier strategies are to truncate the bottom and top 1% or 5% of the distribution. The truncation of the bottom and top 1% (truncate 1%) or 5% (truncate 5%) of the markup distribution reduces the weighted average markup increase.

We apply an alternative strategy that takes both the level and changes in markups over time into consideration. A firm is considered to be an outlier for two reasons. First, in terms of absolute levels, a firm with a markup higher than 15 is considered an outlier. A markup level of 15 is very high, even in this sample. The second rule deals with large changes over time for firms with at least 1 observation of a high markup. To be considered an outlier, the markup has to be higher than 10 in a certain year and this has to be at least 200% higher than the minimum markup and 100% higher than the medium markup of the firm. The second rule is applied to ensure within firm consistency for firms with a very high markup observation (markup value between 10 and 15). This strategy leads to identifying 33 outlier firms (see Appendix A.7.3.A). Deleting these 33 firms leads to a reduction of 11.5% of the sample for each year. The average markup for the outlier group of firms is 33.5 with a standard deviation of 234.1. For the remaining firms, the average markup is 1.7 with a standard deviation of 1.4. The large differences between the two groups and the improbability of the markup levels of the outlier group require an outlier correction, especially when looking at the mean. Excluding the outlier firms leads to a much smaller increase in the markup and leads to the largest difference with the uncorrected markup (See Figure 5.15).

Irrespective of the outlier strategy, the average weighted markup increases over the sample period. However, the difference in the size of the increase is rather large. The average weighted markup has a cumulative growth rate of 13.6% over 15 years for the excluding 33 outliers sample, while the growth rate for the uncorrected sample is 37.4%.

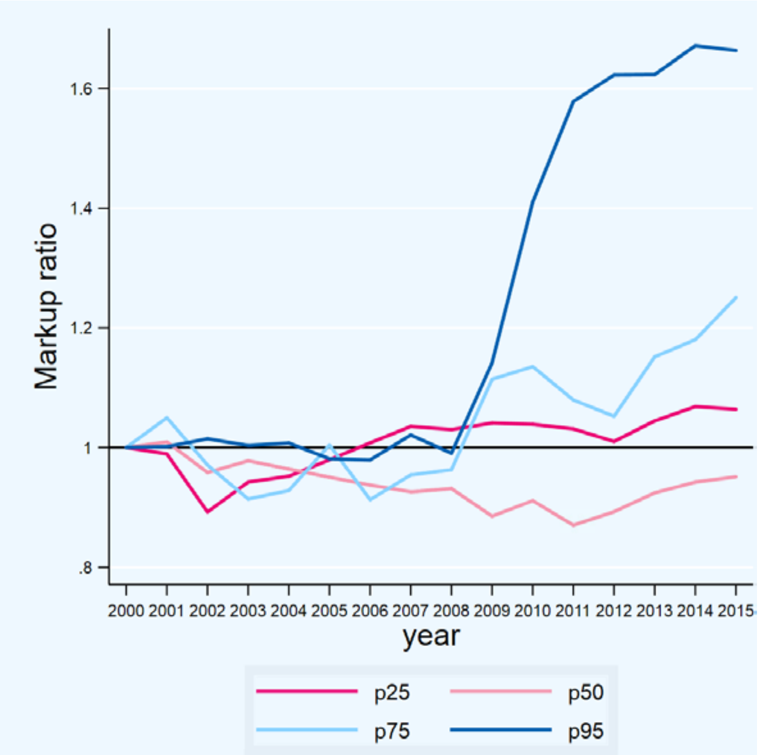
**Figure 5.15: Weighted average markup for different outlier strategies**




Note: **Uncorrected** is the uncorrected markup sample. **Truncate 1%** is the sample when the value below the 1st percentile and above the 99th percentile are deleted from the sample. **Truncate 5%** is the sample when the value below the 5th percentile and above the 95th percentile are deleted from the sample. **Excluding 33 outlier firms** is the sample when the 33 outlier firms are deleted from the sample. The weighted markup is the revenue weighted average markup for the respective sample of firms.

Excluding outliers explains a large portion, but not all, of the difference as markups are still rising for multinationals in Worldscope. Figure 5.16 displays the markup relative to its level in 2000 for percentiles of the weighted markup distribution for the excluding 33 outliers sample. The upper part of the distribution shows more growth than the lower half of the distribution. Nonetheless, all moments, except the median, show an increase in the markup over time, although in varying magnitudes. The increase in the markup is therefore not solely driven by the top of the distribution, although the largest rise is found for these firms. Therefore, there is evidence that markups are increasing for this select sample of firms.

**Figure 5.16: Markup ratio for different markup percentiles (weighted, 2000=1)**




Note: This figure plots percentage changes in the moment of the distribution relative to the level in 2006. Hence, the vertical axis represents the cumulative growth rate from the starting year. Note that the composition of the different deciles changes per year (they do not consist of the same firms for each year) The markup distribution is weighted by revenue, implying that the markups of larger firms dominate the distribution.

Closely related to the outlier strategy is the sample of firms included in the analysis. The sample of firms that are attributed to the Netherlands by Worldscope raise some concerns. The ten largest firms constitute on average 71.4% of the total sales within a year in Worldscope. Over the period 2000-2015, the top ten firms (in revenues) consist of 19 different firms, indicating some switching in the composition of the top ten (See Appendix 7.5). From these 19 firms there are 5 firms that are difficult to link to the Dutch economy.[29] Although this discussion is beyond the scope of this paper, a company like VEON Ltd and Airbus are probably located in the Netherlands for tax reasons. Including these firms distorts, to a certain extent, the markup analysis for the Netherlands.

In sum, the Worldscope sample of firms indicates a rise in the average weighted markup over time that seems to be broad based. The magnitude of the rise depends on the firms that are included in the analysis (i.e. the outlier strategy). The Worldscope data contains a small number of firms that may be located in the Netherlands for tax reasons. When examining the markup level and changes in time, some suspicious markups are identified.

### 5.5.2 Data differences

There are two data factors that can explain the difference between our results and that of De Loecker and Eeckhout (2018a). The first data factor is the choice of the free variable. De Loecker and Eeckhout (2018a) use the costs of goods sold (COGS), while we use material

[29] Airbus, CNH global N.V., Lyondellbasell industries N.V., New world resources PLC, VEON Ltd.

inputs. The COGS in Worldscope is a broad concept that contains, for example, both labour and materials inputs but also the cost of rent and royalty incomes included in revenues. If fixed costs are included in the COGS then this could drive the increase over time (see Loecker et al., 2018b). For example, if labour is considered fixed and these costs are being reduced in large firms over time, then the decreasing trend in these fixed costs could cause the markup of these firms to rise. It is therefore important to exclude all fixed costs incorporated in the free variable to estimate the markup correctly. Labour is often considered fixed in the Netherlands and its costs shares display a decreasing trend, especially for large firms. Including labour and other fixed costs in the free variable could be problematic for the markup analysis. The potential effects of extracting the fixed component from a composite variable are not trivial and can reverse the time trend of the weighted mean markup (See De Loecker et al. 2018b). At the same time, multinationals operate in a number of countries with varying degrees of fixedness in labour input. Therefore, it could be argued that the COGS of multinationals, although containing fixed elements, are more variable, but arguing that they a free remains difficult.

The second data factor concerns the consolidation level of data of multinational firms. The firms in the NFO data are consolidated at the national level. In Worldscope, consolidation at the international level is used whenever possible. This implies that different consolidation levels appear in the Worldscope data depending on how the firms report their data. International consolidated data is available for most Dutch firms present in Worldscope. The advantage of international consolidation is that mismeasurements of costs of intra-company transactions are avoided. For example, transfer pricing can lead to the mismeasurement of markups as revenues and costs will be misreported at a national level. However, De Loecker et al. (2018a) provide evidence, for US firms, that the differences in consolidation level do not lead to a systematic difference. They show that the mean markup based on consolidated accounts is within half a percentage point of the average markup based on domestic data. Therefore, it seems unlikely that consolidation differences are the main cause for different results.

### 5.5.3 Estimating markups for multinationals

We discuss three aspects that complicate estimation of markups for multinational corporations, regardless of the previously mentioned sample and data differences.

Output elasticities cannot be estimated for Dutch multinationals as there are too few observations. De Loecker and Eeckhout (2018a) solve this problem by applying the output elasticity of American publically listed firms to Dutch firms.[30] This approach assumes that Dutch multinationals apply the same production technology as US publically listed firms, although a publically listed firm is not per definition a multinational. Therefore, the direct comparison between the two is not straightforward.[31] It also assumes that labour in the US and the Netherlands is a free input, leading to an applied output elasticity that may be

[30] Equally problematic is the measurement of the output elasticity at a higher level of aggregation (19-super sector level) for all countries as in Diez et al. (2018). A higher level of aggregation increases the possibility that an incorrect output elasticity is applied for the markup calculation of the firm. This will lead to a biased estimation of markups. The direction of the bias is unknown and it could drive the results.

[31] Diez et al (2018) use a different approach and estimate the output elasticity per industry for all countries, which might be a preferred approach. As then similar firms across different countries are compared within an industry.

biased for the Netherlands. Assuming a home bias for multinationals, the composition of the input mix may be different for multinational firms based in different countries leading to differences in the cost shares. How problematic this is depends on how fixed inputs actually are in the countries in which multinational firms are located.

The approach also makes assumptions on the substitutability between (composite) variable inputs. The costs of goods sold (COGS), used as a free input in the papers using the Worldscope and Compustat data, is a broad concept that contains for example both labour and materials inputs. For the international consolidated data, the assumption is made that labour and/or materials, located in the different countries the firm produces in, are perfectly substitutable (see De Loecker and Eeckhout, 2018b). This assumption may not hold, especially when the output elasticity of firms operating in a specific country is used for international consolidated data of multinational corporations. In the case multinational operations are consolidated nationally, the country specific estimated output elasticity should be more applicable. Splitting up the estimation into small and large firms will mitigate the bias (although it still can be claimed that multinational firms produce differently than local firms.)

Finally, the approach assumes that a large firm belongs to a certain (2-digit) sector. However, a multinational often produces multiple goods covering different sectors. In fact, when looking at the 2-digit SIC classification of the 3 main products in terms of revenue that Dutch firms in Worldscope produce, only 51.4% produce goods that are classified in the same 2-digit category. This 51.4% includes firms that only produce one good (23.4%). The majority of firms that produce more than 1 good obtain revenue from products classified in 2 (47.3%) or 3 (16.1%) different 2-digit sectors. Therefore, the applied output elasticity can increase or decrease the markup depending on which sector the firm produces the most output. Switching main sector will influence the markup level, as a different output elasticity is applied. In addition, the cost share and the composition of the cost share can differ over time depending on the importance of the products that a firm produces. Estimating the output elasticity at a lower sector level classification (i.e. 3 or 4 digit) will aggravate the bias. Splitting up the markup calculation of multinational corporations over the different sectors would mitigate bias but unfortunately, this split for production and inputs is not available in the data.

The discrepancy between the markups of multinationals in the microdata and that of Worldscope is not straightforward, it may be contributed to the consolidation at the international level of WorldScope, or the use of a more variable input (materials) in the NFO. Alternatively, both could be incorrectly measured. We can safely conclude that measuring markups for multinationals is complicated. If the increase in the markups is exclusively due to large multinationals, our analysis might underestimate the increase in markups. Never the less, the majority of evidence clearly points in the direction of markups that have not increased in the Netherlands.

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# 7 Appendix

## 7.1 Sectors

**A.7.1.A: Sectors (2-digit SBI 2008) used in the analysis**

| SBI | Description |
|---|---|
| | |
| | **Manufacturing** |
| 10 | Manufacture of food products |
| 13 | Manufacture of textiles |
| 14 | Manufacture of wearing apparel |
| 15 | Manufacture of leather and related products |
| 16 | Manufacture of wood and of products of wood and cork, except furniture |
| 17 | Manufacture of study and study products |
| 18 | Printing and reproduction of recorded media |
| 20 | Manufacture of chemicals and chemical products |
| 21 | Manufacture of basic pharmaceutical products and pharmaceutical preparations |
| 22 | Manufacture of rubber and plastic products |
| 23 | Manufacture of other non-metallic mineral products |
| 24 | Manufacture of basic metals |
| 25 | Manufacture of fabricated metal products, except machinery and equipment |
| 26 | Manufacture of computer, electronic and optical products |
| 27 | Manufacture of electrical equipment |
| 28 | Manufacture of machinery and equipment n.e.c. |
| 29 | Manufacture of motor vehicles, trailers and semi-trailers |
| 30 | Manufacture of other transport equipment |
| 31 | Manufacture of furniture |
| 32 | Other manufacturing |
| 33 | Repair and installation of machinery and equipment |
| | **Services** |
| 45 | Wholesale and retail trade and repair of motor vehicles and motorcycles |
| 46 | Wholesale trade, except of motor vehicles and motorcycles |
| 47 | Retail trade, except of motor vehicles and motorcycles |
| 49 | Land transport and transport via pipelines |
| 50 | Water transport |
| 51 | Air transport |
| 52 | Warehousing and support activities for transportation |

| | |
|---|---|
| 53 | Postal and courier activities |
| 55 | Accommodation |
| 56 | Food and beverage service activities |
| 58 | Publishing activities |
| 59 | Motion picture, video and television program production, sound recording and music |
| 60. | Programming and broadcasting activities |
| 61 | Telecommunications |
| 62 | Computer programming, consultancy and related activities |
| 63 | Information service activities |
| 69 | Legal and accounting activities |
| 70 | Activities of head offices; management consultancy activities |
| 71 | Architectural and engineering activities; technical testing and analysis |
| 72 | Scientific research and development |
| 73 | Advertising and market research |
| 74 | Other professional, scientific and technical activities |
| 75 | Veterinary activities |
| 77 | Rental and leasing activities |
| 78 | Employment activities |
| 79 | Travel agency, tour operator and other reservation service and related activities |
| 80 | Security and investigation activities |
| 81 | Services to buildings and landscape activities |
| 82 | Office administrative, office support and other business support activities |
| | **Other** |
| 1 | Crop and animal production, hunting and related service activities |
| 41 | Construction of buildings |
| 42 | Civil engineering |
| 43 | Specialized construction activities |

## 7.2 Markups

**A.7.2.A: The revenue weighted markup mean (standard deviation) over time**

| Year | Gross output (GO) | GO per size (GO-S) | De Loecker and Eeckhout (DLE) | DLE per size (DLE-S) |
|---|---|---|---|---|
| 2006 | 1.07 (0.90) | 1.10 (0.68) | 1.06 (0.20) | 1.04 (0.18) |
| 2007 | 1.05 (0.89) | 1.08 (0.67) | 1.06 (0.24) | 1.04 (0.22) |
| 2008 | 1.03 (0.83) | 1.06 (0.61) | 1.05 (0.22) | 1.03 (0.20) |
| 2009 | 1.05 (0.86) | 1.08 (0.64) | 1.04 (0.24) | 1.02 (0.22) |
| 2010 | 1.04 (0.78) | 1.08 (0.61) | 1.05 (0.22) | 1.03 (0.20) |

| | | | | |
|---|---|---|---|---|
| 2011 | 1.03<br>(0.81) | 1.06<br>(0.65) | 1.05<br>(0.28) | 1.03<br>(0.26) |
| 2012 | 1.01<br>(0.72) | 1.05<br>(0.56) | 1.04<br>(0.22) | 1.02<br>(0.20) |
| 2013 | 1.02<br>(0.77) | 1.05<br>(0.60) | 1.04<br>(0.22) | 1.02<br>(0.21) |
| 2014 | 1.03<br>(0.84) | 1.06<br>(0.68) | 1.05<br>(0.23) | 1.03<br>(0.22) |
| 2015 | 1.03<br>(0.81) | 1.07<br>(0.64) | 1.06<br>(0.24) | 1.04<br>(0.23) |
| 2016 | 1.04<br>(0.83) | 1.07<br>(0.65) | 1.06<br>(0.25) | 1.04<br>(0.24) |

## 7.3 Potential outlier firms (Worldscope)

**A.7.3.A: Summary statistics of the markups of the 33 outliers**

| name | mean | St. dev. | Median | min | max | N |
|---|---|---|---|---|---|---|
| AERCAP HOLDINGS N.V. | 15.0 | 18.1 | 6.2 | 2.0 | 60.3 | 12.0 |
| AND INTERNATIONAL | 14.8 | 25.8 | 1.8 | 0.7 | 90.3 | 14.0 |
| ARCADIS NV | 4.0 | 5.8 | 1.0 | 0.9 | 15.9 | 16.0 |
| AVG TECHNOLOGIES NV | 10.8 | 6.2 | 8.3 | 4.6 | 23.0 | 8.0 |
| BASIC FIT NV | 134.4 | 6.4 | 134.4 | 129.8 | 138.9 | 2.0 |
| BNP PARIBAS OBAM NV | 4.4 | 3.8 | 2.1 | 1.5 | 12.6 | 9.0 |
| COLUMBIA SECURITIES | 4.5 | 4.6 | 3.4 | 0.4 | 15.7 | 12.0 |
| CORIO NV | 7.3 | 3.3 | 7.6 | 4.2 | 17.7 | 15.0 |
| DIM VASTGOED NV | 5.8 | 3.6 | 4.5 | 2.7 | 11.9 | 8.0 |
| EUROPEAN ASSETS | 9.5 | 7.9 | 8.2 | 1.3 | 21.4 | 11.0 |
| FORTUNA ENTERTAIN | 2086.1 | 2353.1 | 2086.1 | 422.2 | 3750.0 | 2.0 |
| HOLLAND FUND | 5.8 | 5.7 | 3.8 | 1.9 | 15.8 | 5.0 |
| INNOCONCEPTS NV | 4.7 | 4.8 | 3.2 | 1.5 | 17.5 | 10.0 |
| INTEREFFEKT JAPANSE | 7.3 | 7.3 | 6.0 | 0.0 | 17.3 | 4.0 |
| INTERTRUST NV | 179.2 | 183.2 | 179.2 | 49.7 | 308.7 | 2.0 |
| LEVERAGED CAP HLDGS | 197.9 | 423.6 | 71.7 | 15.8 | 1466.7 | 11.0 |
| MCC GLOBAL NV | 16.9 | 28.3 | 3.3 | 1.8 | 59.3 | 4.0 |
| MKB NEDSENSE NV | 11.9 | 12.6 | 3.3 | 1.0 | 30.5 | 13.0 |
| NN EQUITY INVEST | 99.1 | 333.2 | 2.6 | 0.6 | 1157.1 | 12.0 |
| NV BEVER HOLDING | 18.7 | 1.1 | 18.7 | 17.9 | 19.5 | 2.0 |
| ORANGE GLOBAL | 27.1 | 57.3 | 6.0 | 3.6 | 168.8 | 8.0 |
| ORIX CORPORATION | 4.8 | 6.7 | 1.8 | 1.3 | 20.4 | 10.0 |
| PHARMING GROUP NV | 2.4 | 3.8 | 1.3 | 0.0 | 13.7 | 13.0 |
| QMULUS N.V. | 21.4 | 27.8 | 8.5 | 4.3 | 75.7 | 6.0 |
| ROBECO GLOBAL | 29.3 | 84.9 | 4.4 | 3.6 | 311.5 | 13.0 |
| ROLINCO NV | 9.0 | 21.6 | 1.2 | 0.0 | 66.4 | 16.0 |
| TELEGRAAF MEDIA | 4.3 | 4.1 | 1.6 | 1.4 | 12.2 | 16.0 |

| | | | | | | |
|---|---|---|---|---|---|---|
| TIE KINETIX NV | 3.9 | 3.7 | 1.4 | 0.8 | 12.0 | 13.0 |
| TNT EXPRESS NV | 9.0 | 12.0 | 1.5 | 1.3 | 34.0 | 8.0 |
| UNIT4 NV | 4.9 | 4.5 | 1.4 | 1.1 | 11.5 | 14.0 |
| VASTNED RETAIL NV | 7.9 | 4.6 | 6.8 | 5.6 | 25.1 | 16.0 |
| WERELDHAVE NV | 5.6 | 3.7 | 3.9 | 1.4 | 13.1 | 16.0 |
| WS VASTGOED WESTER | 14.0 | 1.1 | 13.9 | 12.8 | 15.2 | 4.0 |

## 7.4 Largest firm in revenues per sector (Worldscope)

Only 13 companies remain the largest in their sector over time (see Table 7.4). For the remaining 36 sectors, the largest firm in 2015 is different from the one in 2000. The dominance of the largest firm in terms of total sector revenue, however, remains fairly stable with 76.7% in 2000 and 79.1% in 2015. The sectors with a change of the largest firm have seen major shifts in market shares over time. Another explanation for the change in largest firm is that a certain amount of sample selection has taken place over time, leading to the exiting and entering of firms. For example, KLM disappears from the sample after the merger with Air France.

#### A.7.4.A: Largest firm in revenues per sector

| SIC | Name firm (2000) | % rev. | Name firm (2015) | % rev. |
|---|---|---|---|---|
| 1 | | | ASTARTA HOLDING NV | 1.00 |
| 2 | | | OVOSTAR UN | 1.00 |
| 10 | | | NORD GOLD SE | 0.54 |
| 12 | | | NEW WORLD RESOURCES PLC | 1.00 |
| 13 | ROYAL DUTCH SHELL PLC | 0.94 | ROYAL DUTCH SHELL PLC | 0.98 |
| 15 | HOLLANDSCHE BETON GROEP NV | 0.54 | KONINKLIJKE BAM GROEP NV | 0.57 |
| 16 | KONINKLIJKE VOLKER WESSELS STEVIN NV | 0.25 | CHICAGO BRIDGE & IRON COMPANY N.V. | 0.57 |
| 17 | NV GTI HOLDING | 1.00 | | |
| 20 | HEINEKEN HOLDING | 0.27 | HEINEKEN NV | 0.46 |
| 23 | VELCRO INDUSTRIES NV | 0.64 | | |
| 25 | HUNTER DOUGLAS NV | 0.96 | HUNTER DOUGLAS NV | 1.00 |
| 26 | CROWN VAN GELDER NV | 1.00 | | |
| 27 | RELX NV | 0.53 | RELX NV | 0.82 |
| 28 | UNILEVER N.V. | 0.64 | UNILEVER N.V. | 0.48 |
| 29 | ROYAL DUTCH PETROLEUM COMPANY | 1.00 | | |
| 30 | GAMMA HOLDING NV | 0.55 | HYDRATEC INDUSTRIES NV | 1.00 |
| 32 | JAMES HARDIE INDUSTRIES PLC | 0.88 | JAMES HARDIE INDUSTRIES PLC | 0.98 |
| 33 | ARCELORMITTAL | 0.52 | CONSTELLIUM NV | 0.63 |
| 34 | AALBERTS INDUSTRIES NV | 0.37 | AALBERTS INDUSTRIES NV | 1.00 |
| 35 | CNH GLOBAL N.V. | 0.76 | ASML HOLDING NV | 0.90 |
| 36 | KENDRION NV | 0.73 | SIGNIFY NV | 0.48 |
| 37 | AIRBUS SE | 1.00 | AIRBUS SE | 0.98 |
| 38 | KONINKLIJKE PHILIPS NV | 0.91 | KONINKLIJKE PHILIPS NV | 0.88 |

| | | | | |
|---|---|---|---|---|
| 39 | HEAD NV | 1.00 | | |
| 42 | KONINKLIJKE VOPAK NV | 1.00 | TNT EXPRESS NV | 0.83 |
| 43 | POSTNL | 1.00 | POSTNL | 1.00 |
| 44 | KONINKLIJKE P&O NEDLLOYD NV | 0.93 | | |
| 45 | KLM ROYAL DUTCH AIRLINES | 1.00 | | |
| 47 | KONINKLIJKE FRANS MAAS GROEP N.V. | 1.00 | | |
| 48 | KONINKLIJKE KPN NV | 0.94 | ALTICE EUROPE NV | 0.48 |
| 49 | SHV HOLDINGS N.V. | 0.94 | DGB GROUP NV | 0.80 |
| 50 | CORPORATE EXPRESS N.V. | 0.47 | ROYAL REESINK NV | 1.00 |
| 51 | SUPER DE BOER | 0.43 | SLIGRO FOOD GROUP NV | 0.39 |
| 52 | MAVERIC CAPITAL NV | 1.00 | | |
| 54 | KONINKLIJKE AHOLD DELHAIZE NV | 0.95 | KONINKLIJKE AHOLD DELHAIZE NV | 1.00 |
| 55 | STERN GROEP NV | 1.00 | STERN GROEP NV | 1.00 |
| 56 | GUCCI GROUP N.V. | 0.60 | | |
| 57 | MAXEDA | 0.91 | BETER BED HOLDING NV | 1.00 |
| 58 | | | AMREST HOLDINGS SE | 1.00 |
| 59 | MEDIQ NV | 1.00 | GRANDVISION NV | 1.00 |
| 60 | EASE2PAY NV | 1.00 | | |
| 62 | EURONEXT NV | 0.85 | FLOW TRADERS NV | 0.54 |
| 65 | RODAMCO EUROPE NV | 0.26 | WERELDHAVE N.V. | 0.28 |
| 67 | HAL TRUST | 0.48 | HAL TRUST | 0.99 |
| 73 | VEDIOR NV | 0.23 | RANDSTAD NV | 0.49 |
| 75 | ATHLON HOLDING N.V. | 1.00 | | |
| 79 | AFC AJAX NV | 0.54 | BASIC FIT NV | 0.61 |
| 80 | ISOTIS NV | 1.00 | ESPERITE NV | 1.00 |
| 87 | ROYAL IMTECH NV | 0.72 | ARCADIS NV | 0.81 |

## 7.5 List of top ten firms over 2000-2015 (Worldscope)

#### A.7.5.A: List of top ten firms over 2000-2015

| COMPANY NAME | Average % tot. rev. share when in data | Freq. In the top 10 |
|---|---|---|
| AIRBUS SE | 5.8% | 16 |
| AKZO NOBEL N.V. | 11.9% | 12 |
| ARCELORMITTAL | 7.0% | 5 |
| CNH GLOBAL N.V. | 2.1% | 1 |
| HEINEKEN HOLDING | 5.8% | 8 |
| HEINEKEN NV | 5.8% | 10 |
| KONINKLIJKE AHOLD DELHAIZE NV | 14.9% | 16 |
| KONINKLIJKE KPN NV | 5.7% | 9 |
| KONINKLIJKE PHILIPS NV | 2.2% | 16 |
| LYONDELLBASELL INDUSTRIES NV | 4.2% | 8 |
| NEW WORLD RESOURCES PLC | 14.5% | 1 |
| NV NEDERLANDSE GASUNIE | 25.9% | 3 |

| | | |
|---|---|---|
| POSTNL | 5.0% | 4 |
| RANDSTAD NV | 1.6% | 4 |
| ROYAL DUTCH PETROLEUM COMPANY | 4.3% | 5 |
| ROYAL DUTCH SHELL PLC | 34.9% | 16 |
| SHV HOLDINGS N.V. | 2.0% | 8 |
| UNILEVER N.V. | 12.2% | 16 |
| VEON LTD | 3.9% | 2 |

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