
# Price Markups, Innovation, and Productivity: Evidence from Germany

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# Price Markups, Innovation, and Productivity: Evidence from Germany

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# Zusammenfassung


Produktivität wird allgemein als treibende Kraft für das Wirtschaftswachstum und als Indikator für den materiellen Wohlstand einer Gesellschaft angesehen. Jedoch haben viele Industrieländer in den letzten Jahrzehnten ein rückläufiges Produktivitätswachstum und eine Ausweitung der Produktivitätsspreizung erlebt. Mögliche Erklärungen reichen von rückläufigen Investitionen in Forschung und Entwicklung über strukturelle Veränderungen im Hinblick auf Verschiebungen hin zu mehr Dienstleistungen bis hin zu vermehrten Messfehlern durch die zunehmende Digitalisierung. In diesem Bericht untersuchen wir die Rolle, die das Wettbewerbsumfeld eines Unternehmens für die eigene Produktivitätsentwicklung spielt. Ist eine zunehmende Branchenkonzentration – und der damit einhergehende erwartete Rückgang des Wettbewerbs – mit geringerer Produktivität verbunden? Und wenn ja, was ist die treibende Kraft dieses Effekts?

In einem ersten Schritt schätzen wir die Preis-Kosten-Margen auf Firmenebene in Form von *Markups* (Preisaufschläge, d.h., Preis über den Grenzkosten) als Maßzahl für die Preissetzungsmacht eines Unternehmens und den Grad des Wettbewerbs, dem es ausgesetzt ist. Unsere Ergebnisse basieren auf Daten von knapp 12.000 deutschen Unternehmen für den Zeitraum 2007 bis 2016.

1. Die durchschnittlichen Markups liegen bei 30-45 Prozent und sind vergleichsweise niedriger als in größeren Industrienationen wie den USA, entsprechen jedoch den durchschnittlichen Schätzungen für Europa. Über den Zeitraum der Stichprobe zeigt sich ein leicht positiver Trend der durchschnittlichen Markups. Die Finanzkrise hatte im Gegensatz zu den USA lediglich einen geringen negativen Effekt auf die durchschnittlichen Markups in Deutschland. Der Dienstleistungssektor war treibende Kraft für diesen Rückgang der durchschnittlichen Markups in den Jahren 2007-2009; andere Sektoren wie das verarbeitende Gewerbe und der Handelssektor verspürten keine derartigen Auswirkungen.

2. Kleinere Unternehmen weisen im Durchschnitt höhere Markups auf – eine Beobachtung, die in den meisten Branchen zu finden ist. Eine potenzielle Erklärung für diese Beziehung zwischen Markups und Unternehmensgröße ist die Breite des Geschäftsfeldes eines Unternehmens. Unternehmen mit einem engen Geschäftsfokus, die nur in wenigen Märkten aktiv sind (*Nischenunternehmen*, die im Durchschnitt kleiner sind), weisen höhere Markups auf als Unternehmen mit einem breiteren Geschäftsfokus.

3. Höhere Markups sind über die gesamte Unternehmensverteilung zu beobachten. Sowohl kleine als auch große Unternehmen (aber nicht mittelgroße Unternehmen) verzeichnen während der Finanzkrise einen Rückgang der Markups, jedoch weisen gegen Ende unseres Messzeitraums lediglich große Unternehmen Markups über dem Vorkrisenniveau auf. Die „Erholung“ war für kleinere Unternehmen langsamer und weniger effektiv.

Neben der vorangegangenen deskriptiven Beschreibung der Markup-Entwicklung untersucht die vorliegende Studie den Zusammenhang zwischen Markups und Produktivität.

4. Markups erklären die Produktivitätsentwicklung der verschiedenen Sektoren in unterschiedlichem Maße. Im verarbeitenden Gewerbe und im Handel ist der Effekt stark. Die Streuung der Preisaufschläge erklärt etwa 20 Prozent der Produktivitätsunterschiede im verarbeitenden Gewerbe und mehr als 40 Prozent im Handelssektor. In dienstleistungsbezogenen Sektoren ist der Effekt mittelstark – die Variation der Produktivität auf Unternehmensebene, die auf Preisaufschläge zurückzuführen ist, beträgt hier 6 Prozent.

5. Bei Unternehmen aus dem verarbeitenden Gewerbe und Handelssektor sind höhere Markups mit geringerer Produktivität verbunden. Dieser Zusammenhang ist über die Zeit konstant. In diesen Sektoren sinkt die Produktivität durchschnittlich um 1,4 Prozent als Reaktion auf einen Anstieg der Preisaufschläge um 1 Prozent. Die Auswirkungen sind für den Handelssektor (mit einem Rückgang von 4 %) stärker als für das verarbeitende Gewerbe (mit einem Rückgang von 2 %). Die Ergebnisse für Unternehmen in Dienstleistungssektoren sind dagegen umgekehrt: Eine Erhöhung der Markups hat einen geringen, jedoch positiven Effekt auf die Produktivität der Unternehmen.

Der geschätzte Zusammenhang von Markups und Produktivität stellt den *kombinierten* Effekt dar. Die Hinzunahme von Unternehmensdaten aus dem Mannheimer Innovationspanel des ZEW erlaubt eine differenzierte Betrachtung der direkten (z. B. via Managementpraktiken) und indirekten (über veränderte Innovationsaktivitäten) Einflüsse der Markups auf Produktivität. Für diese Analyse wird eine Teilstichprobe von rund 1.900 Unternehmen herangezogen.

6. Im verarbeitenden Gewerbe sowie im Handelssektor ist der direkte Effekt negativ und entspricht dem allgemeinen Konsens, dass verschärfter Wettbewerb die Produktivität erhöht. Im Dienstleistungssektor hingegen ist der geschätzte direkte Effekt positiv. Dies deutet auf einen gegenteiligen Effekt hin: Ein verschärfter Wettbewerb im Dienstleistungssektor hat einen negativen Einfluss auf die Produktivitätsentwicklung.

7. Im verarbeitenden Gewerbe und im Dienstleistungssektor ist der indirekte Effekte von Markups auf Produktivität negativ; weniger Wettbewerb senkt die Produktivität. Dies liegt darin begründet, dass eine Verringerung des Wettbewerbsdrucks einen negativen Einfluss auf die Innovationsaktivität hat. Eine Einsparung der Innovationsausgaben wiederum wirkt sich negativ auf die Produktivitätsentwicklung aus. Im verarbeitenden Gewerbe ist der indirekte Effekt gering und verstärkt den ohnehin negativen direkten Effekt. Im Dienstleistungssektor hingegen ist der negative indirekte Effekt stark und gleicht den positiven direkten Effekt teilweise aus. Für den Handelssektor ist der indirekte Effekt nicht signifikant. Das bedeutet, dass die Innovationstätigkeit im Handelssektor nicht als Wirkungskanal des Wettbewerbs (oder dem Fehlen eines solchen) auf die Produktivität agiert.

Die Erkenntnis, dass Markups starke direkte Auswirkungen (im Vergleich zu den innovationsorientierten indirekten Auswirkungen) in allen Sektoren außer dem Dienstleistungssektor haben, unterstreicht das Potenzial wettbewerbspolitischer Maßnahmen, die auf eine Minderung des Produktivitätsrückgangs abzielen. Dies gilt insbesondere für den Handelssektor. Im Dienstleistungssektor hingegen muss die Interdependenz von Wettbewerb und Innovation in ihrer Auswirkung auf die Produktivität berücksichtigt werden. In diesem Fall gleicht der indirekte Effekt den direkten Effekt teilweise aus. Daher ist stets eine gemeinsame Betrachtung beider Effekte notwendig, um eine fundierte und aufschlussreiche Analyse wettbewerbspolitischer Maßnahmen vornehmen zu können.

# Abstract

Productivity is seen as a driving force behind economic growth and an indicator of a society's material wellbeing. Over the past decades, however, many industrialized countries have experienced declining productivity growth and an expansion of the productivity differential. Possible explanations range from declining investment in R&D to structural changes to more services and increased measurement errors due to increasing digitalization. In this report, we study the role that a firm's competitive environment plays for its own productivity development. Is an increase in industry concentration – and the expected decrease in competition – associated with lower productivity? And what is the underlying driving force of this effect?

We estimate firm-level price-cost margins in the form of price markups (i.e., price above marginal cost) as a proxy for a firm's pricing power and the degree of competition that it is exposed to. We obtain results using data from a sample of 12,000 German firms over the period of 2007 through 2016.

1. Average price markups across all industries are at 30-45 percent, and thus lower than what has been found for the United States but in line with estimates for Europe. Over the course of our sample, markups exhibit a slight positive trend. Unlike in the United States, the financial crisis had only a small negative effect on price markups in Germany. The decline in economy-wide average markups in 2007-2009 was driven by effects in services, whereas the manufacturing and trade sectors did not experience any such effects.

2. We find that smaller firms exhibit, on average, higher price markups – a pattern we observe in most sectors. One potential factor for this relationship between price markups and firm size is the degree of competitive exposure from a broader rather than a narrower business focus. We find that firms with a narrow business focus that are active in only a few markets (*niche firms* that are on average smaller) exhibit higher markups than firms with a broader business focus.

3. We observe an increase in price markups across the entire firm-level distribution – not simply a further increase in markups by firms that already exhibit relatively high markups. Both small and large firms (but not medium-sized firms) show a decline in price markups during the financial crisis, but at the end of our sample period only large firms have markups above the pre-crisis levels. The "recovery" for small firms has been slower and less effective.

We further examine the relationship between price markups and productivity – with the goal of explaining future productivity with price markups.

4. Price markups explain productivity to varying degrees across different industries. The effect in manufacturing and trade is strong, with firm-level variation in markups explaining about 20 percent of the variation in productivity in the manufacturing sector and more than 40 percent in the trade sector. In services-related sectors, the effect is of medium strength – the variation in firm-level productivity that is attributable to price markups is 6 percent.

5. For firms in the manufacturing and trade sectors, we find that higher markups are associated with lower productivity, a relationship that is constant over time. Our estimates suggest that productivity decreases by about 1.4 percent in response to a 1 percent increase of price markups. The effects are stronger for the trade sector (with a 4% decrease) than in manufacturing (with a 2% decrease). The results for firms in ser-

vice-related sectors are reversed: an increase in price markups has a small but positive effect on firm-level productivity.

The estimated baseline effects of price markups on productivity are *combined* effects. Using firm-level innovation data from the ZEW's Mannheim Innovation Panel for a subsample of about 1,900 firms, we can separately estimate a direct effect of price markups on productivity (e.g., via managerial practices) and an indirect effect (by way of a firm's innovation activities that are a function of price markups).

6. In the manufacturing and trade sectors, the direct effect is negative and in line with the conventional view that more competition increases productivity. In the services sector, on the other hand, the estimated direct effect is positive, suggesting that more competition in that sector has a dampening effect on productivity.

7. The indirect effect of price markups on productivity is negative in the manufacturing and services sector – more competition lowers productivity because it lowers innovation expenditure which in return lowers productivity. In manufacturing, the indirect effect is relatively small and reinforces the negative direct effect. In services, on the other hand, the negative indirect effect is sizable and partially offsets the positive direct effect. For the trade sector, we do not find a significant indirect effect and conclude that a firm's innovation activity does not contribute to the effect of competition (or the lack thereof) on productivity.

Our findings of relatively strong direct effects of price markups (in comparison to the innovation-centered indirect effects) in all sectors but services highlight the potential for a well-tailored competition policy approach in society's effort to tackle the productivity slowdown.

This is particularly true for the trade sector, where the effect of competition on R&D and innovation is of limited significance for the determination of firm-level productivity. For services, on the other hand, the interdependence of competition and innovation in their effect on productivity must be taken into account as the indirect effect partially offsets the direct effect of competition on productivity. Considering one without the other will be misguiding.

# Content

# 1 Introduction

## 1.1 Background

Productivity is seen as a driving force behind economic growth and as an indicator of a society's material wellbeing. Over the past decades, however, many industrialized countries have experienced declining productivity growth and an expansion of the productivity differential (Peters et al., 2018). This development is also relevant for Germany, where a slowdown of total factor productivity growth has been observed for the second half of the last century, with a more serious development since the beginning of the 2000s. The academic literature has responded with a revived interest in the sources of this decline in productivity growth (e.g., Bloom et al., 2020)[1]. Possible explanations range from declining investment in R&D to structural changes to more services and increased measurement errors due to increasing digitalization. In this report, we study the role that a firm's competitive environment plays for its own productivity development. Is an increase in industry concentration – and the expected decrease in competition – associated with lower productivity? And what is responsible for this effect?

A first glimpse at data for the United States seems to support such a relationship. While productivity growth has slowed down, industry concentration as well as firms' market power have seen an upward trend. For instance, Grullon et al. (2019) find that at least 75 percent of all U.S. industries have experienced an increase in concentration. They attribute this trend to lax interpretation and application of competition policy rules on the one hand and to increased technological barriers to entry on the other hand. They conclude that this increase in concentration has resulted in a decrease in competition. Similarly – and providing an increase in market power as an explanation – for the U.S., De Loecker et al. (2020) document an increase of price-cost margins from 21 percent (1980) to 61 percent (2016).

The conventional view in the literature (particularly in the literature on competition economics and policy) is that higher industry concentration (or higher price markups) has a negative effect on productivity. Put differently, if industry concentration is taken to serve as a proxy for market power (and underlying weaker competition),[2] then we would expect a positive relationship between competition and productivity (or: a negative relationship between markups and productivity). Responsible for this link are a *direct effect* (when technology is taken as given) and an *indirect effect* (when endogenizing the level of technology that is available to firms).

A key mechanism for the direct effect of competition on productivity that has been put forward is the idea that competition induces firms to *adopt* more efficient processes and practices – given their availability. A lack of competition reduces this incentive, an effect that has become known as the "quiet-life hypothesis" (Hicks, 1935) or as the notion of "X-inefficiency" (Leibenstein, 1966).[3] Recent empirical work finds support for this mechanism.[4] An alternative explanation for the positive relationship is a "Darwinian mechanism" (Motta, 2004) where the less productive firms

1 A comprehensive review of this literature can be found in Peters et al. (2018)

2 For a discussion of the (theoretical) positive relationship between the average degree of market power (and lower competition) and the degree of industry concentration (measured as the Herfindahl-Hirschman Index, HHI), see for instance Motta (2004:123-4). In a recent review of the literature, Wessel (2018:109) concludes that "preponderance of evidence across the proliferating body of research suggests that industry consolidation is causing a troubling decline in competition, limiting the country's capacity to innovate, create jobs, and sustain overall economic health."

3 More recent theoretical work by, for instance, Hart (1983) and Schmidt (1997) is in line with this early literature.

4 Schmitz (2005) concludes that in the U.S. iron ore industry, higher productivity was a result of investment in new management practices; Matsa (2011) argues that retailers, facing increased competition after entry of Wal-Mart in a local market, increased productivity through investment in inventory control; Bloom et al. (2019) find a positive relationship between competition and strong management practices (inducing higher productivity). Other examples are Nickell (1996), Caves and Barton (1990), Green and Mayes (1991), or Backus (2019).

are driven out of the market – for competitive industries more so than for highly concentrated ones. Asplund and Nocke (2006), for instance, provide a theoretical framework to that effect, and empirical support for this explanation can be found in Olley and Pakes (1999), Disney et al. (2003), Syverson (2004), or Backus (2019).[5] Both explanations yield a negative (causal) relationship between price markups and productivity.

Other strands of the literature, however, have argued (and found) a *positive* relationship. De Loecker and Warzynski (2012:2463) allude to models in industrial organization that predict that more productive firms (with lower marginal costs) are able to charge higher markups, *ceteris paribus.*[6] They indeed find a highly significant and positive relationship between price markups and productivity. Similar results can be found in Altomonte et al. (2018), who estimate a markup-productivity elasticity of 1.2 to 1.4.[7] A different argument for a positive markup-productivity relationship is brought forward by Autor et al. (2020) who find evidence for rising industry concentration that is the result of increased productivity. They argue that technological changes give rise to more concentrated markets (with "superstar firms") as the most productive firms get more sales. The result is more product market concentration, and markets are dominated by superstar firms with higher price markups. A similar argument is put forward by Hsieh and Rossi-Hansberg (2019) who find that higher concentration is the result of more efficient firms competing in more localized markets.

5 A third explanation is by Neven and Röller (1996). They argue that, under weaker competition, firms are more likely to share rents with their stake holders, which has a negative effect on productivity. Similar conclusions can be drawn from Dunne et al. (2010) who show that in the cement industry the productivity-increasing investment was in the form of renegotiation of work rules and contracts.

6 The authors acknowledge that marginal cost may in fact be a bad proxy for productivity, citing Katayama et al. (2009) and De Loecker (2011). To see that the conjectured relationship is critically dependent on key structural assumptions of the models, consider the inverse-elasticity rule for monopoly pricing, $\frac{(p-c)}{p}=\frac{1}{\eta}$ where $p$ is the price, $c$ the firm's marginal cost, and $\eta$ the price elasticity of demand. $\frac{(p-c)}{p}$ is called the Lerner index. We can rearrange this rule to obtain an expression for markups used by De Loecker and Warzynski (2012) (as well as in this report): $\frac{p}{c}=\frac{\eta}{\eta-1}$. For instance, under a constant-elasticity demand function in a monopoly, a change in marginal costs (productivity) will have no effect on the firm's markup, as the markup is constant (and determined by price elasticity $\eta$ only).

7 Both author teams estimate this relationship with price markups as dependent left-hand side variable and productivity as independent right-hand side variable in their estimation specifications. We will take a different approach, assuming productivity as the dependent variable and (lagged) price markups as explanatory variable.

The indirect effect of price markups on productivity is by way of innovation. The vast majority of empirical studies has shown that innovation has a positive effect on productivity (Hall, 2011; Mohnen and Hall, 2013; Peters et al., 2017). The evidence on how competition affects innovation, on the other hand, is much more complex and less clear. Theoretical models show that under certain conditions, competition can increase investment in innovation while under different conditions competition reduces incentives to innovate. Two seminal contributions with diverging conclusions are Schumpeter (1934) and Arrow (1962) (also, see Gilbert (2006) for a review of the literature). According to Schumpeter, innovation incentives increase with ex ante market power. Firms with greater market power are better able to finance R&D through own profits, can more easily appropriate the returns from innovation, and they face lower uncertainty associated with excessive rivalry that tends to reduce the incentive to innovate. On the contrary, Arrow argues in favor of competition being conducive for innovation since an incumbent monopolist would sacrifice his own current profits and has thus a lower incentive to innovate than an entrant (Arrow's "replacement effects"). The model by Aghion et al. (2005) combines these countervailing effects and establishes an inverted-U relationship: Competition fosters innovation in industries where firms operate at the same technological level (neck-and-neck), whereas in technologically unleveled industries increased competition lowers innovation incentives for laggard firms.

A few recent contributions have shown a positive effect of competition on innovation. Aghion et al. (2018), for instance, provide results on a causal relationship between competition and innovation from laboratory experiments. Haucap et al. (2019) find that, after a merger, both the merging entities and their competitors innovate less, especially in markets with high pre-merger R&D intensity. Igami and Uetake (forthcoming) exploit the consolidation of the hard disk drive industry to establish a causal link, and Bloom et al. (2016) use Chinese imports as a proxy for competition faced by European firms. They show that firms facing higher levels of Chinese import competition apply for more patents, raise their IT intensity, and increase their overall level of productivity. However, Autor et al. (forthcoming), taking the same approach, show that for publicly listed companies in the U.S., increased competitive pressure reduced investment in R&D and decreased output of innovation (measured by patent grants).

## 1.2 Aim and Structure

In this study, we address the question of the relationship between price markups and productivity, emphasizing the different roles of direct and indirect effects. To obtain a measure for competition, we follow the approach by De Loecker and Warzynski (2012) and estimate price markups for the years 2007 through 2016 from a sample of more than 12,000 German firms.[8] Interpreting higher price markups as evidence for less competition (or less exposure to competition), we are able to study the relationship between competition and productivity *at the firm level.*[9] We complement this information with firm-level innovation data from the Mannheim Innovation Panel to separate the direct effect of competition on firm-level productivity (holding innovation constant) from the indirect effect (by way of endogenous innovation).

After describing our empirical set-up in Section 2 and the data in Section 3, we present our main results in three sections: In Section 4, we provide a detailed account and summary of our estimated price markups. In Section 5, we examine the simple relationship between price markups and productivity – keeping innovation constant. In Section 6, we explicitly model innovation as both a determinant of productivity and a function of price markups to separately estimate the direct effect and the indirect effect of price markups (as proxy for competition) on productivity.

## 1.3 Key Findings

We find that average price markups across all (included) industries in Germany are at 30-45 percent and thus significantly lower than for the U.S. (De Loecker et al., 2020), but in line with estimates for Europe (De Loecker and Eeckhout, 2018; Cavalleri et al., 2019). Over the course of our sample, markups exhibit a positive trend. The financial crisis did not have a strong negative effect on economy-wide average price markups in Germany, although we observe sector-specific differences of the effects. Price markups in manufacturing (which are at economy-wide average levels) and trade (which are below average levels) did not decline during the financial crisis, whereas markups in services (which are above economy-wide average) dropped by roughly 20 percentage points, but more than bounced back since. Furthermore, we observe an increase in price markups across the entire firm-level distribution – not simply a further increase in markups by firms that already exhibit high markups.

We further show that smaller firms exhibit, on average, higher price markups – a pattern we observe in most industries. One potential explanation for this relationship between price markups and firm size is the degree of competitive exposure from a broader rather than a narrower business focus. We find that firms with a narrow business focus that are active in only a few markets (*niche firms* that are on average smaller) exhibit higher markups than firms with a broader business focus.

We find mixed results for the association of productivity and price markups across different sectors. First, price markups explain productivity to varying degrees. The effect size for firms in manufacturing, where firm-level variation in markups explains about 20 percent of the variation in productivity, and in the trade sector, where this number increases to almost 40 percent, is large (Cohen, 1988). In services, where the percentage of the variation in firm-level productivity that is attributable to price markups is a 6-7 percent, the effect size is medium.

Second, for firms in manufacturing and trade, we find that higher markups are associated with lower productivity, and this relationship is fairly constant over time. When using lagged price markups to explain concurrent firm-level productivity, we estimate (negative) productivity-markup elasticities of about 2.2 (manufacturing) and 3.8 (trade), meaning that a 1 percent increase in price markups results in a 2.2 percent decrease in firm-level productivity. These results imply that more competition is associated with higher productivity. Our results for manufacturing and trade are in line with the “quiet-life hypothesis” (Hicks, 1935) or the notion of “X-inefficiency” (Leibenstein, 1966) and comport with recent empirical findings (Schmitz, 2005; Matsa, 2011; Bloom et al., 2019; Backus, 2019). For services, we find mixed results – depending on the productivity measure used in our estimations. The positive productivity-markup elasticity we find when using labor

8 This approach has been used in a large number of papers. A few examples are Edmund et al. (2015), De Loecker and Scott (2016), Altomonte et al (2018), Stiebale and Vencappa (2018), Weche and Wambach (2018), van Heuvelen et al. (2019), Autor et al. (2020), and De Loecker et al. (2020).

9 We present most of our results as the relationship between productivity and markups. Throughout the paper, however, we keep the working assumption that higher markups are associated with less competition and higher industry concentration. This assumption allows for the interpretation of our results as “relationship between productivity and competition” or “relationship between productivity and industry concentration” and thus provides for a better link to the existing literature discussed above.

productivity comports with the arguments brought forward by Autor et al. (2020) or Hsieh and Rossi-Hansberg (2019).

In a last step, we explore a firm's innovation activity as an additional potential indirect channel through which price markups affect firm-level productivity. We estimate a system of equations (one explaining productivity as a function of markups and innovation and one explaining innovation as a function of markups) and obtain estimates for the direct effect of price markups on productivity and the indirect effect by way of innovation. In manufacturing and trade, the direct effect is negative and in line with the conventional view that more competition increases productivity. In the services sector, the estimated direct effect is positive and at odds with the conventional view but in line with the work by Autor et al. (2020) or Hsieh and Rossi-Hansberg (2019). The indirect effect of price markups on productivity is negative in the manufacturing and services sector – more competition lowers innovation expenditure which in return lowers productivity. In manufacturing, the negative indirect effect is relatively small but reinforces the negative direct effect. In services, on the other hand, the negative indirect effect is sizable and partially offsets the positive direct effect. For the trade sector, we do not find a significant indirect effect and conclude that a firm's innovation activity does not contribute to the effect of competition (or the lack thereof) on productivity.

# 2 Constructing Price Markups and Measures for Productivity

In this section, we discuss the construction of the key variables for our main analysis. We estimate *price markups* as a measure of a firm's price-cost margin. This measure both captures a firm's ability to raise prices above marginal cost *(market power)* and, when averaging over the entire industry, serves as a proxy for industry concentration.[10] Both concepts are related to the degree of competition. Higher price markups (suggesting more market power for the firm) are typically associated with weaker competition (within the firm's market) to which the firm is exposed. Likewise, higher industry concentration (that is, concentration of the market in which the firm is active) is associated with weaker competition. Following the approach by De Loecker and Warzynski (2012), we obtain price markups at the firm level, which allows us to study the firm's response to its exposure to competition (or lack thereof) as well as the industry's overall degree of competition. The *response* we are interested in is the firm's productivity, that is, the efficiency of its use of input factors to produce output. We also construct and estimate two different measures of productivity: labor productivity and total factor productivity.

## 2.1 Price Markups

For the purposes of this report, we define the price markup as the ratio of output prices $P_{it}$ over marginal production cost $MC_{it}$ where $i$ is the index for a firm and $t$ is time:

$$(1)\quad \mu_{it} = \frac{P_{it}}{MC_{it}}$$

10 For a discussion of the use of price markups (or, the Lerner index) as a measure for market power, in particular in the context of competition policy, see Motta (2004:115-7). Using simple oligopolistic models (e.g., a Cournot model with $n$ firms that produce a homogeneous good at constant marginal cost), one can show that the average degree of market power (measured as the price markup or Lerner index) is directly and positively related to the degree of industry concentration (measured as the Herfindahl-Hirschman Index, HHI). For the formal steps, see Motta (2004:123-4).

One characteristic of this definition is that any values above unity imply above-marginal-cost pricing associated with some degree of a firm's market power.[11] For instance, a markup value of 1.5 means that the firm operates at a 50 percent markup. In the sequel, we briefly introduce the approach we take to obtain price markup data at the firm level. More details including a discussion of the limitations of this approach can be found in the appendix.

Price markups are not directly observed in any firm-level data but have to be estimated. Our estimation of price markups closely follows De Loecker and Warzynski (2012). They use a cost-minimization framework to recover price markups as a function of the output elasticity of a variable production factor (e.g., labor) and the cost share of that production factor (over the firm's revenue).[12] Both components can be estimated using firm-level financial data. It is this latter feature and the fact that the approach is not very data demanding that makes it attractive for empirical analysis.

For the estimation of price markups, we begin by assuming that firms produce with a given production technology, represented by a function $Q_{it}(\cdot)$:

$$(2)\quad Q_{it} = Q_{it}(X^1_{it}, \ldots, X^V_{it}, K_{it}, \omega_{it})$$

11 This definition is different from the more commonly used one in, for instance, the literature of industrial organization. In this literature, price markups are often defined through the Lerner index, that is, the ratio between the profit margin $P_{it}-MC_{it}$ and the price $P_{it}$ (Tirole, 1988:66).

12 In principle, the choice of labor or material as the variable production factor should not affect the estimation results. In a recent (and unpublished) working paper, Raval (2019) rejects this notion, finding that markups estimated using labor and materials do not exhibit the same distributions. Van Heuvelen et al. (2019) also apply both approaches with divergent results. They argue these differences may stem from adjustment costs otherwise not accounted for in the estimation.

Output $Q_{it}$ is function of $1, \ldots, V$ variable inputs $X_{it}^{v}$ the capital stock $K_{it}$, and an unobserved productivity measure $\omega_{it}$. Given the prices for input factors $(P^{X_{it}^{v}})$ as well as the price for capital $r_{it}$, and given a fixed output level, firms choose a mix of production factors to minimize their production costs. We can represent the firm's cost minimization problem in the form of a Lagrangian:

$$(3)\quad L(X_{it}^{1}, \ldots, X_{it}^{V}, K_{it}, \omega_{it}) = \sum_{v=1}^{V} P_{it}^{X^{v}} X_{it}^{v} + r_{it} K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot))$$

For a given level output $Q_{it}$, the Lagrange multiplier $\lambda_{it}$ represents the marginal costs of production $MC_{it}$. The first-order condition with respect to a variable input $X_{it}^{v}$ can therefore be used to recover the firm's price markup:

$$(4)\quad \frac{\partial Q_{it}}{\partial X_{it}^{v}} \frac{X_{it}^{v}}{Q_{it}} = \frac{1}{\lambda_{it}} \frac{P_{it}^{X^{v}} X_{it}^{v}}{Q_{it}}$$

The left-hand side of this equation is the output elasticity with respect to the variable input $X_{it}^{v}$. We denote this output elasticity by $\theta_{it}^{v}$. After some algebraic manipulation, price markups, denoted by $\mu_{it}$, can be expressed as:

$$(5)\quad \mu_{it} = \frac{P_{it}}{\lambda_{it}} = \theta_{it}^{v} \left( \frac{P_{it}^{X^{v}} X_{it}^{v}}{P_{it} Q_{it}} \right)^{-1} = \frac{\theta_{it}^{v}}{\alpha_{it}^{v}}$$

A firm's price markup is therefore equal to the output elasticity $\theta_{it}^{v}$ of a variable input and the cost share $\alpha_{it}^{v}$ (over the firm's revenue) of that input. The former we obtain from an estimated production function (following the approach in Ackerberg et al. (2015)), the latter from financial statements.

## 2.2 Productivity Measures

We use two measures for productivity: labor productivity and total factor productivity (TFP). Both measures are meant to capture how efficient input factors are converted into outputs (Hulten, 2001).

Our first measure is *labor productivity.* A broad body of literature (Gal, 2013:17) defines labor productivity as gross output $Y_{it}$ divided by labor (e.g., number of employees) $L_{it}$:

$$\textit{Labor Productivity}_{it} = \frac{Y_{it}}{L_{it}}$$

Higher values of this measure imply higher levels of output per unit of labor – simply translating into higher productivity of labor.[13] We make adjustments to this measure in two directions. First, we do not observe physical output $(Y)$ but use sales revenue (turnover) as a proxy for physical output. Our labor productivity measure is thus defined as:

$$(6)\quad \textit{Labor Productivity}_{it} = \frac{\textit{Revenue}_{it}}{L_{it}}$$

Second, we apply a correction of sales revenue to control for random shocks.[14] By the first adjustment, our labor productivity measure is revenue based. This is relevant when studying the relationship between productivity and price markups (as proxy for competition), as markups can be associated with both production efficiency as well as revenue efficiency. For instance, as predicted by Hicks (1935) or Leibenstein (1966), higher markups are associated with less production-efficient firms. At the same time, however, higher markups are also expected to be associated with higher revenue (given constant output), implying higher revenue-efficiency. These two channels give rise to an ambiguous effect of price markups on productivity when using a revenue-based measure. To address this problem, we also use total factor productivity, which we obtain from our production function estimates.

For our second measure, we follow De Loecker and Warzynski (2012:2463) and derive a total factor productivity measure as by-product of our production-function estimation (as the first step of the estimation of price markups). It is the difference between the estimated expected output of firm and the predicted output for the firm using the estimated production function coefficients. This difference must then be the unexplained productivity of firm i. This second productivity is to a lesser degree subject to the same revenue effects as labor productivity and allows us to consider productivity from a different angle.

13 Note that factors such as process innovation or new management practices are likely to affect labor productivity.

14 It is the same correction applied to the labor cost share in the context of price-markup construction, as described in equation (32) in the appendix, following De Loecker and Warzynski (2012:2449).

# 3 Data Sample for Markup Estimation

For our estimation of price markups, we use data from Germany for the years 2006 through 2016.[15] We obtain our main estimation sample from Bureau van Dijk's Orbis database.[16] Relevant for our purposes of estimating price markups and productivity measures, the database contains balance sheet as well as income statements. We further collect information on a company's industry classification and the legal form. In Table 1, we provide a list of the respective variables and their definitions.

## 3.1 Sample Construction

Our estimation sample is an unbalanced panel over the period 2006 to 2016 and comprises 11,963 firms with an average number of 6,629 firms per year. When interpreting the following results, one should keep in mind that our sample is selective. Sample selection is due to two reasons. First, legal reporting rules imply that small firms are generally underrepresented.[17] And second, we impose the following sampling restrictions that are partly driven by our chosen methodology:

1. We include data only from unconsolidated accounts.
2. Firms with missing values for any of the variables listed in Table 1 are dropped from our sample. Moreover, we include only firms with at least 20 employees[18] and firms that report turnover (revenue) of at least 100,000 euros per year.

TABLE 1: **Variable Definitions**

| Variable Name | Description |
|---|---|
| Sales (Output Y) | Net sales or turnover |
| Number of employees (Labor L) | Total number of employees on the company's payroll |
| Cost of employees (Labor costs LC) | All costs of employees (including pension costs) |
| Tangible fixed assets (Capital K) | Tangible assets (buildings, machinery, etc.) |
| Material costs (Material costs M) | Costs of goods purchased (including raw materials and finished goods but excluding services) |
| Nace Rev. 2 main section | Nace main section |
| Nace Rev. 2, Primary code(s) | Primary four-digit Nace code (group) reported |
| Nace Rev. 2, Secondary code(s) | Secondary four-digit Nace code (group) reported (if applicable) |
| Legal form | Reported national legal form of the company |
| Region | German federal state *(Bundesland)* |

List of variables obtained from Bureau van Dijk's Orbis database, with the variable name as used in Orbis and a short description of the data. We also provide the respective notation used for the description of the markup estimation in Section 2.

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15 Because of the use of one-year lagged variables in our price-markup estimation procedure, we obtain values for price markups for the years 2007 through 2016.

16 For Germany, Bureau van Dijk obtains its data from Creditreform and Creditreform Rating AG. The database covers approximately 63 percent of all German firms (Kalemli-Ozcan et al., 2015).

17 Medium sized and large firms are obligated to report balance sheet information, a statement of income, and notes on the accounts. Small firms are exempt from the reporting requirements of a statement of income. Following the definition in §267 Handelsgesetzbuch, firms are assigned to each of these size categories if at least two of the following criteria are satisfied. For *small* firms: number of employees ≤ 50; turnover ≤ 9,680,000 euros; total assets ≤ 4,840,000 euros. For *medium* firms: between 50 and 250 employees; turnover between 9,680,000 euros and 38,500,000 euros; total assets between 4,850,000 euros and 19,250,000 euros. For *large* firms: more than 250 employees; turnover > 38,500,000; total assets > 19,250,000. These definitions were in place until 2015. We use them for our entire sample.

18 With respect to the coverage of Orbis as a function of the number of employees, Calligaris et al. (2018) find: "Current analysis comparing administrative data sources and Orbis confirms indeed that for the group of firms employing more than 20 workers, Orbis covers a larger portion of the population of firms than for the sample including firms of all sizes"

3. We restrict our estimation sample to firms from 8 Nace Rev.2 sections: manufacturing, trade, and 6 business-related services sections that we combine to a "services" sector.[19]
4. Our sample period is from 2006 through 2016.[20]
5. We include only firms with observations for at least two consecutive years. This stems from a requirement of our estimation procedure.
6. We drop firms that exit and later re-enter our raw sample.[21]
7. We drop observations that are imputed by Bureau van Dijk (most prominently in the years 2012–2014).
8. In order to remove outliers that might drive our estimation results, we winsorize our sample by dropping observations with values of *capital* and *material costs* in the upper and lower 0.5 percentiles and values of *output* in the upper 0.1 percentile.[22]

Our sample does not contain data on physical inputs and output (except for the number of employees). Instead, we observe the necessary variables in terms of their value in euros. To render observations comparable across time, we deflate all monetary values that are reported in nominal euros. We provide more information on our approach (including sources for our deflators) in the appendix.

## 3.2 Basic Descriptive Statistics of Estimation Sample

Our estimation sample exhibits a fairly stable number of firms per year – both for the full sample and for each sector – for the years 2007 through 2015. The first (2006) and the last (2016) years in our sample, however, come with a significantly smaller number of firms and observations.[23] At the sector level, we observe large differences in absolute sample size. In Table 2, we provide the number of firms and number of observations for sectors manufacturing, trade, and services. Manufacturing and trade are the two most populated sectors (Nace sections).

TABLE 2: **Number of Firms and Observations by Sector (Nace Section)**

| Nace Section | Firms | Observations |
|---|---|---|
| Manufacturing (C) | 5,435 | 33,942 |
| Trade (G) (Wholesale and retail trade) | 3,671 | 22,521 |
| Services (Nace sections H, I, J, L, M, and N) | 2,857 | 16,453 |
| Total | 11,963 | 72,916 |

The table contains the total number of firms and the total number of observations for Nace sections Manufacturing (C), Trade (G) and the combined services (Nace sections H, I, J, L, M, and N). In Table 17 in the appendix, we provide numbers for each individual Nace Section used in the estimation sample.
Source: Numbers based on data obtained from Bureau van Dijk's Orbis database and authors' own calculations.

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The vast majority of firms in our sample are limited liability companies (*GmbH* or *GmbH & Co. KG*). About 92 percent of our sample firms have this legal form. Only a small share of 5 percent of all firms in the sample are corporations or public limited companies (*Aktiengesellschaft*, AG). We provide a breakdown of our sample by legal form in Table 3.[24]

In Table 4, we provide basic descriptive statistics of the main variables used in our analysis. The average firm in our sample has (deflated) revenue of more than 90 million euros, a capital stock (tangible assets) of 14 million euros, and about 315 employees. It incurs 15 million euros for its labor input and 51 million for its material input. Moreover, 78 percent of the observations in our sample are by firms that report a secondary Nace code indicating that these firms operate in multiple markets.

As mentioned earlier, our estimation sample is not necessarily representative of the sample contained in the Orbis database. In Table 4, we further report results from balancing tests, comparing the means of our variables of interest across samples. All reported differences are statistically

19 The 8 Nace sections are: Manufacturing (C); Wholesale and retail trade (G); Transportation and storage (H); Accommodation and food service activities (I); Information and communication (J); Real estate activities (L); Professional, scientific and technical activities (M); and Administrative and support service activities (N). In the appendix, we further provide some results for sections Mining and quarrying (B); Electricity, gas, steam, and air conditioning supply (D); Water supply, sewerage, waste management (E); and Construction (F). For more information on Nace Rev.2, see the Eurostat manual at https://ec.europa.eu/eurostat/documents/3859598/5902521/KS-RA-07-015-EN.PDF.

20 We restrict our sample to exclude the years before 2006 due to the unavailability of producer price indices (used to deflate our data) for specific sectors.

21 The reverse does not apply: we retain firms that enter and later exit our sample.

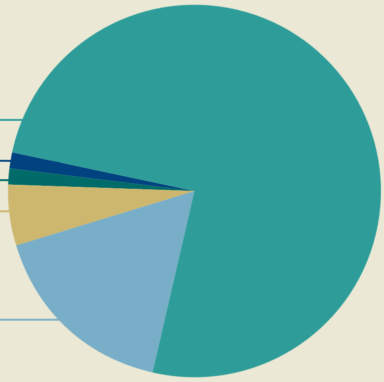
22 Here, we follow best practice approaches. See, for instance, Hall and Mairesse (1995).

23 Estimated values at the boundaries of our sample are therefore to be treated with caution.

24 Legal form is constant. We do not observe any changes of legal form throughout our sample period.

TABLE 3: **Number of Firms by Legal Form**

| Legal Form | Firms | % |
|---|---|---|
| Limited liability company (GmbH) | 9,005 | 75.3 |
| GmbH & Co. KG | 2,014 | 16.8 |
| Corporation / PLC (AG) | 616 | 5.2 |
| Registered cooperative | 184 | 1.5 |
| Other | 144 | 1.2 |
| Total number of firms | 11,963 | 100.0 |



The table lists the number of firms in our estimation sample by their legal form. The figure on the right visualizes these numbers. Numbers based on data obtained from Bureau van Dijk's Orbis database and authors' own calculations.
Source: Numbers based on data obtained from Bureau van Dijk's Orbis database and authors' own calculations.

TABLE 4: **Sample Difference**

| | Estimation | | Orbis | | |
|---|---|---|---|---|---|
| Variable | Mean | Std. dev. | Mean | Std. dev | Difference |
| Revenue (in mio.) | 91.81 | 219.90 | 27.72 | 591.90 | 64.09 *** |
| Capital stock (in mio.) | 14.20 | 67.55 | 6.27 | 125.80 | 7.93 *** |
| Employees | 313.60 | 1,984.00 | 88.52 | 1,234.00 | 225.10 *** |
| Labor costs | 15.84 | 85.92 | 8.96 | 118.90 | 6.88 *** |
| Material costs | 51.51 | 108.60 | 46.71 | 969.40 | 4.80 *** |
| Secondary Nace code reported | 0.78 | 0.42 | 0.75 | 0.43 | 0.03 |
| Observations | 72,916 | | 184,919 | | |

The table reports means and standard deviations and provides a comparison of our main variables for our estimation sample and the Orbis raw sample.
The last column lists the difference in means. Revenue, capital stock, and input costs (in monetary values) are in 1,000,000 (deflated) euros. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Source: Numbers based on data obtained from Bureau van Dijk's Orbis database and authors' own calculations.

different from zero. Our estimation sample comprises firms that have higher revenue, that are larger (in both assets and employment), and that pay more for their labor and input compared to the Orbis raw sample. This selection of larger companies into our estimation sample ought to be taken into account when interpreting the results of this report.[25]

25 This selection problem is not unique to our report but applies to other studies using Orbis (or similar) data. Note that whether or not this non-representativeness has implications for how representative of all German firms our estimation sample remains an open question.

# 4 Estimated Price Markups for Germany (2007–2016)

In this section, we present our estimates for price markups for Germany in the years 2007 through 2016. For the estimation, we use the number of employees as variable input, take a structural value-added approach with a Cobb-Douglas production function, and estimate production functions at the sector level.[26] For the results presented in this section, we trim the 1st and 99th percentile.[27]

## 4.1 Time Trends for Price Markups

In Figure 1, we present average price markups obtained for our estimation sample (for manufacturing, trade, and services). The blue line depicts simple (arithmetic) means, whereas the green line depicts revenue-weighted averages. The former represents the price markups of a typical – or "average" – firm. Moreover, revenue-weighted average markups (as representation of the average markup taking the weight of the respective firm into account) are defined as

$$(7)\quad Average\ markup_t = \sum_i \frac{Y_{it}}{\sum_j Y_{jt}} \cdot Markup_{it} = \sum_i \frac{Y_{it}}{Y_t} \cdot \mu_{it} = \sum_i s_{it} \cdot \mu_{it}$$

where $Y_{it}$ is firm revenue in $t$. The denominator $\sum_j Y_{it}$=$Y_t$ denotes the sum of revenues of all firms $j$ in year $t$ so that the fractional expression captures a firm's revenue-based market share $s_{it}$.

We find that, on average across all sectors, price markups in Germany range between approximately 30-45 percent.[28] These values fall within the range of estimates reported by other authors. De Loecker and Eeckhout (2018) find average price markups of 35 percent for Germany in 2016. Cavalleri et al. (2019) estimate average markups in Germany of about 15 percent for the time period covered in this report – and similar values for Europe. Moreover, our estimates are significantly lower than those reported for the U.S. For instance, De Loecker et al. (2020) estimate price markups of 61 percent (for 2016), and Autor et al. (2020) find markups of 80 percent (for 2012).

Our results add a number of new or refined observations. First, we see a weak decline during the financial crisis – at the beginning of our sample period – for the revenue-weighted averages (our main measure of interest). Note, however, that this observation is very sector-specific and driven by services. We provide more details further below.

Second, the revenue-weighted average shows an increase of price markups by about 12 percentage points since 2009. Recall from our earlier discussion that our estimation sample comprises a significantly smaller number of observations in the first and last year of our sample window. When excluding the first and last year from our markup estimates (and thus relying on the years with larger numbers of annual firm observations), we must conclude that price markups in Germany have seen a very moderate increase. Our point estimates show an increase of about 4 percent between 2009 and 2015 (or 2 percent between 2007 and 2015). This observation is consistent with the findings by Weche and Wambach (2018) or Cavalleri et al. (2019) who find fairly stable markups. De Loecker and Eeckhout (2018), on the other hand, estimate an increase of price markups (for Europe) by 26 percent for the period of 2010 through 2016, a significantly stronger increase than what we observe for Germany in that same time period.

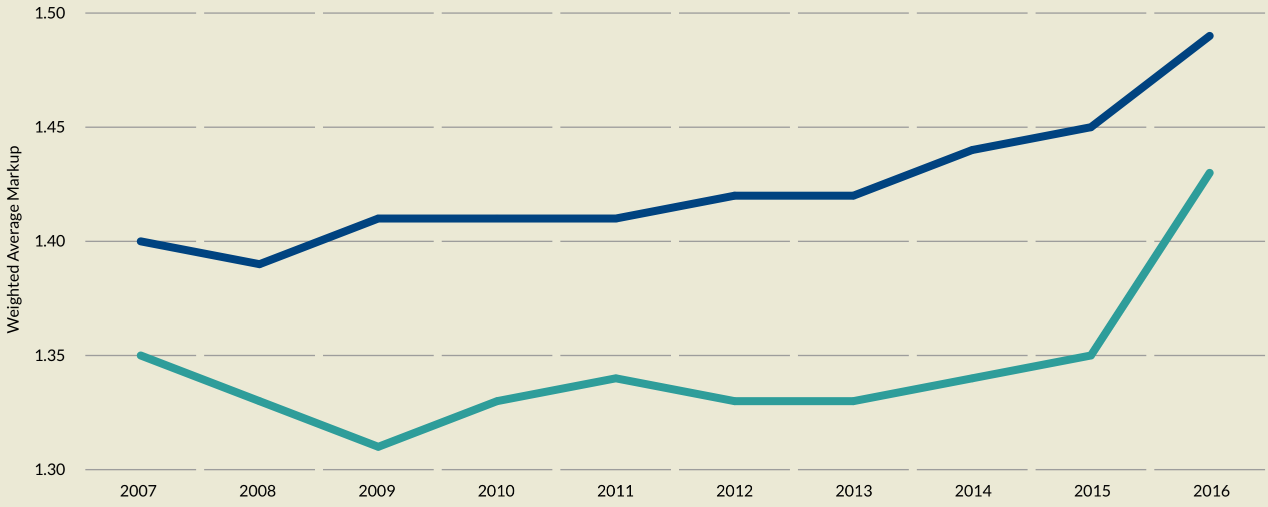
Third, we observe that revenue-weighted averages of price markups are lower than the simple means. This implies higher markups for firms of smaller size. We provide more evidence of this further below. We also observe that markups for the average firm (i.e., the simple mean) and

26 For more implementation details, see the appendix.

27 This approach is a common practice to eliminate the influence of outliers on the results (Weche and Wambach, 2018; van Heuvelen et al., 2019; De Loecker et al., 2020).

28 We consider these figures for the revenue-weighted averages more relevant as large firms with more sales (and higher impact on consumers and the economy as a whole) enter with more weight.

FIGURE 1: **Average Price Markups**




Weighted average markup    Arithmetic average markup

The figure presents the average price markups for manufacturing, trade, and services. The green line depicts average price markups weighted by firms' revenue, $\mu_t = \Sigma_i s_{it} \mu_{it}$ with $s_{it} = \frac{Y_{it}}{Y_t}$ and $Y_t = \Sigma_j Y_{jt}$; the blue line depicts a simple (arithmetic) mean. For the calculation of price markups, we use the coefficients from sector-specific production function estimates using a structural value-added approach with a Cobb-Douglas production function. For the calculation of means, estimated price markups are winsorized (bottom and top percentile).
Source: Authors' own calculations.

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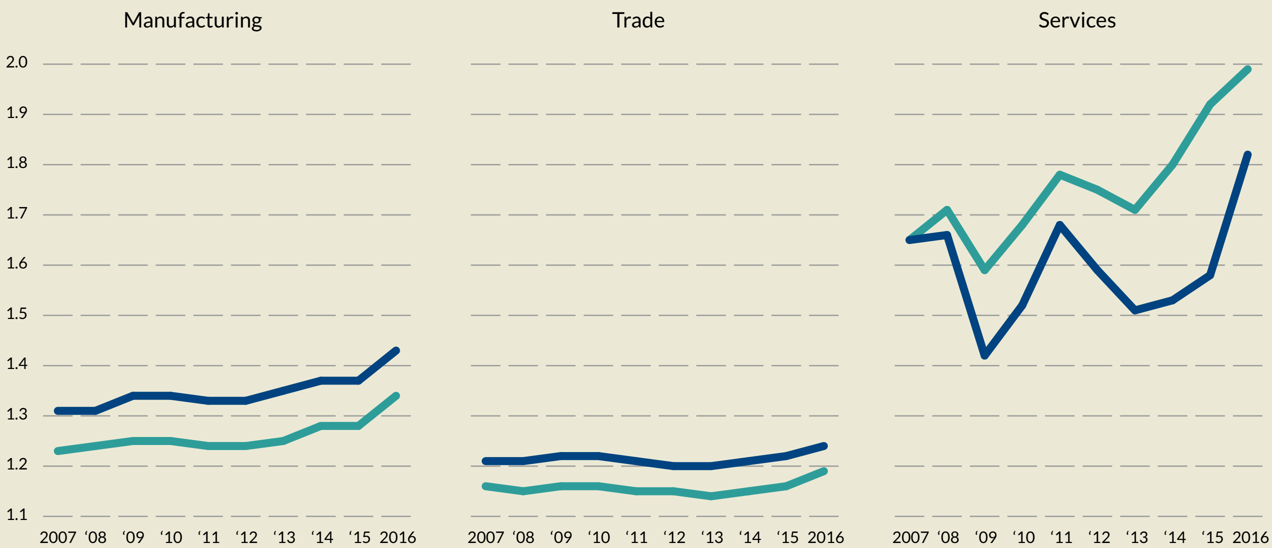
FIGURE 2: **Average Price Markups by Sector (Nace Section)**




Section specific    Uniform

The figure presents the revenue-weighted average price markups (with weights calculated at the sector level) for manufacturing, trade, and services. Blue lines depict the results for estimates from sector-specific production functions; green lines depict the results from the assumption of a uniform production function across all sectors. For more estimation details, see the notes for Figure 1.
Source: Authors' own calculations.

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aggregate markups (i.e., the weighted average) grow at similar pace. We therefore do not find any support for the prediction and findings in Autor et al. (2020), where aggregate markups rise more quickly because of increasing market shares and markups for the largest firms (e.g., "superstar firms").

The observations from Figure 1 hold for our total estimation sample, averaging across manufacturing, trade, and services – each with their sector-specific production technologies and competitive environments. Observed patterns, however, are very sector-specific. We explore this in Figure 2, where we present average price markups separately for each of the three sectors. The blue line depicts these sector-specific price markups. Compared with the economy-wide average markups (30-45%), we find higher markups in services (60-85%) and lower markups for trade (15-20%). Price markups for manufacturing are at economy-wide average levels. This last finding is inconsistent with the results in Cavalleri et al. (2019) who find lower than average markups in manufacturing.

Examining the time trends, we observe stronger than average trends for manufacturing and a fairly stable development of markups over time for trade. For services, we see a decline of price markups of more than 20 percentage points during the financial crisis in 2007-2009 (in the early years of our sample period), a pattern we do not observe for manufacturing or trade. The initial decrease in economy-wide average markups observed in Figure 1 is therefore fully attributable to services. In fact, the services sector did not recover from the drop in price markups during the financial crisis until 2015.

The green lines in Figure 2 depict average price markups when assuming a uniform production technology across all sectors. The juxtaposition of markups based on sector-specific production technologies (our preferred method) and the alternative with uniform technologies allows us to examine the estimation "bias" from using a uniform production technology across all sectors. We observe significantly higher price markups for sector-specific production technologies than for uniform technologies in manufacturing and trade and lower markups in services. Moreover, without a sector-specific approach, the decline in markups during the financial crisis would be significantly smaller in size.

## 4.2 Price Markups by Firm Size

In Figure 3, we present results for price markups for different firm sizes: small (blue lines), medium (green lines), and large (yellow lines). In panel (a) on the left we plot levels of markups, whereas in panel (b) on the right we plot the cumulative change in markups.

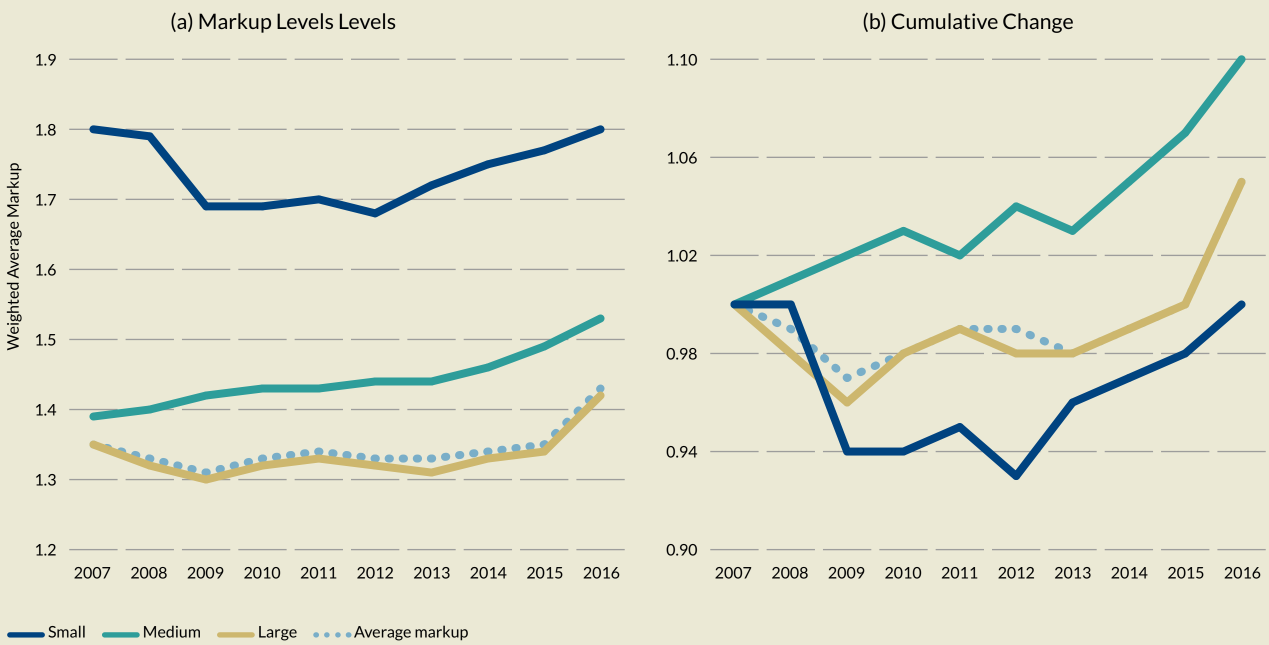
From the left panel of Figure 3, we can see that price markups decrease in firm size: smaller firms exhibit higher markups than large firms.[29] Price markups of small firms as well as large firms are affected the most by financial crisis in 2007-2009, whereas medium-sized firms do not exhibit any decrease in markups during that period. In fact, markups are monotonically increasing throughout our sample period. Price markups for small firms drop from 80 percent in 2007 to below 70 percent in 2012 before increasing back to pre-crisis level in 2016. We observe a similar pattern for large firms that return to pre-crisis markup levels in 2015.

One potential driver behind the markup level patterns by firm size are differences across sectors. For instance, only 8 percent of firms that qualify as small firms belong to the trade sector, compared to 26 percent and 30 percent in medium firms and large firms, respectively. Trade is also a sector with low average price markups. This distributional pattern implies lower markups for larger-sized firms. Note, however, that these patterns across sectors cannot fully explain the differences in the markup levels across firm-size group as we observe the same firm-size patterns *within* sectors. In Table 5, we report average markups by sector and firm size. Average price markups are decreasing in firm size for all three sectors.

Another potential explanation of why small firms exhibit higher level of markups is that those small firms compete in more specialized niche markets (with lower degrees of competition). In Figure 4, we plot average markups (panel (a) on the left) and the cumulative change (panel (b) on the right) for firms that report only a primary 4-digit Nace group (green lines) as well as firms that report both a primary and secondary group (blue lines). The former subsample of firms we consider as more specialized firms being active in relatively niche markets. On average, 22 percent of firms in our sample belong to this group of specialized firms. We see that specialized firms exhibit

29 Note that average markups (dotted lines in Figure 3) trace the markups for large firms. This is because average markups are revenue-weighted, with markups of large firms with higher weights.

FIGURE 3: **Average Price Markups by Firm Size**




The figures depict the revenue-weighted average price markups in panel (a) and the cumulative change in panel (b) (with 2007=1) for three different firm-size categories. Data are for manufacturing, trade, and services. For more estimation details, see the notes for Figure 1. Size classes are defined based on § 267 Handelsgesetzbuch, see Footnote 17 in Section 3.1.
Source: Authors' own calculations.

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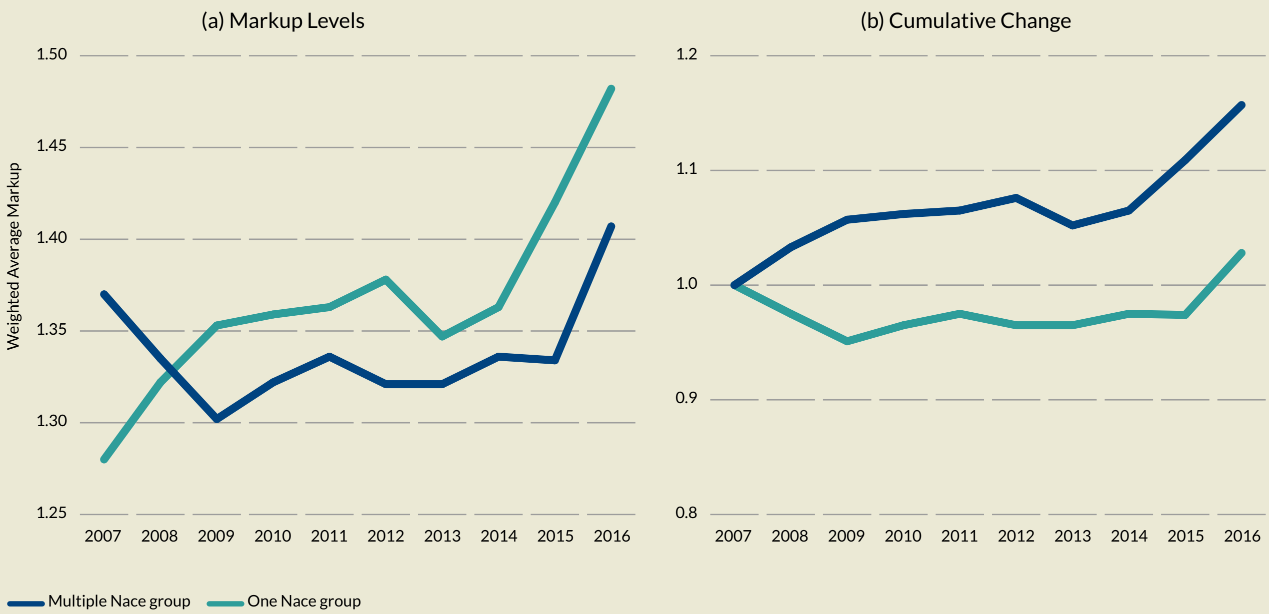
FIGURE 4: **Average Price Markups by Degree of Specialization**




The figures depict the revenue-weighted average price markups (panel (a)) and the cumulative change (panel (b), with 2007=1) for firms reporting only a primary 4-digit Nace group (green lines) as opposed to firms that report both a primary and secondary group (blue lines). Data are for manufacturing, trade, and services. Size of subsamples varies over time. Average number of firms with only a primary reported Nace group: 1,294. Average number of firms with both a primary and a secondary reported Nace group: 4,394.
Source: Authors' own calculations.

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higher markups than firms with broader business activities (in panel (a) on the left). With specialized firms on average being smaller than firms with broader business activities, this result adds another potential explanation to why small firms exhibit higher markups.

## 4.3 Firm-Level Distribution of Price Markups

In order to obtain a better understanding of markup trends at the firm level, in Figure 5, we plot kernel density estimates of the firm-level distributions of unweighted price markups for the years 2007 (blue line) and 2016 (green line). We find that the variance of the firm-level distribution has increased. We can further see from the figure that the distribution as a whole has shifted to the right. We thus observe a general increase in price markups across all levels of price markups, and not simply a further increase in markups by firms that already exhibit high markups.

Kernel density estimates of unweighted markups, of course, do not account for revenue weights. In order to better compare distributional differences to our revenue-weighted average price markups (presented, for instance, in Figure 1), we plot different moments of the distribution of revenue-

TABLE 5: **Average Price Markups by Sector and Firm Size**

| | Firm Size | | |
|---|---|---|---|
| Nace Section | Small | Medium | Large |
| Manufacturing | 1,561 | 1,410 | 1,342 |
| Trade | 1,779 | 1,284 | 1,206 |
| Services (Nace sections H, I, J, L, M, and N) | 1,869 | 1,700 | 1,573 |

The table reports revenue-weighted average price markups by sector for three different firm size categories. Data are for manufacturing, trade, and services. For the definitions for firm size, see Footnote 17. For more estimation details, see the notes for Figure 1. Authors' own calculations.
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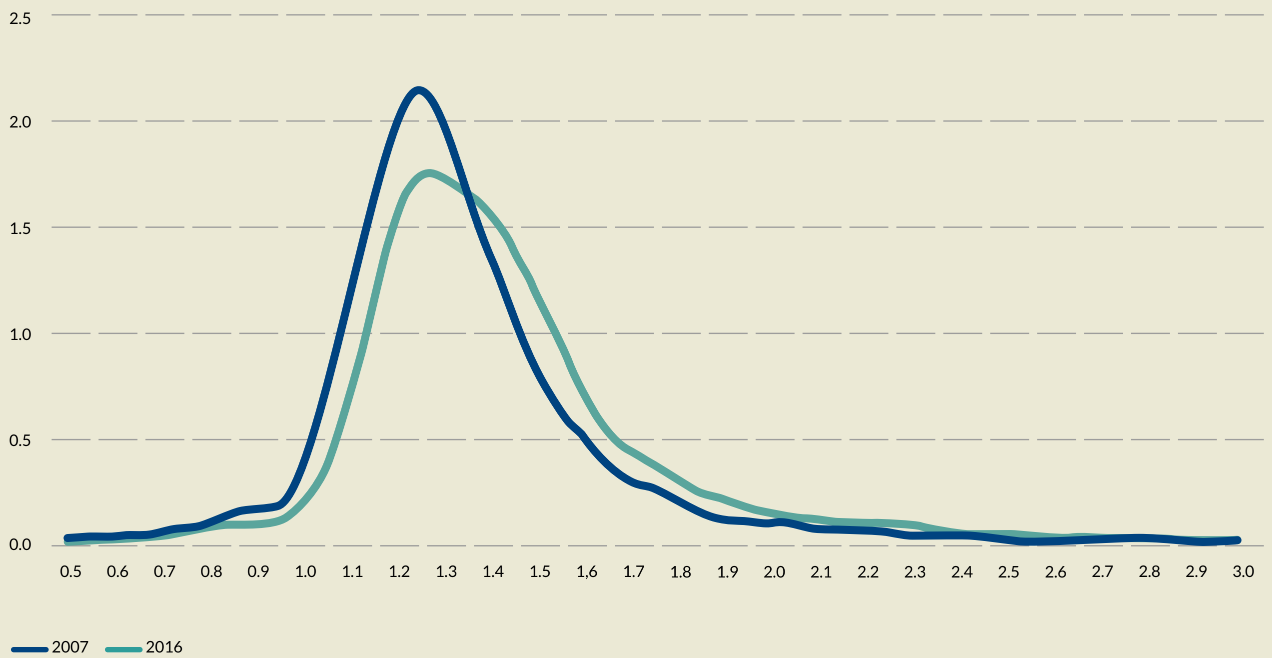
FIGURE 5: **Firm-level Distribution of Price Markups**




This figure depicts kernel density plots of the distributions of unweighted price markups for firms in 2007 (blue line) and 2016 (green line) for manufacturing, trade, and services. For more estimation details, see the notes for Figure 1.
Source: Authors' own calculations.

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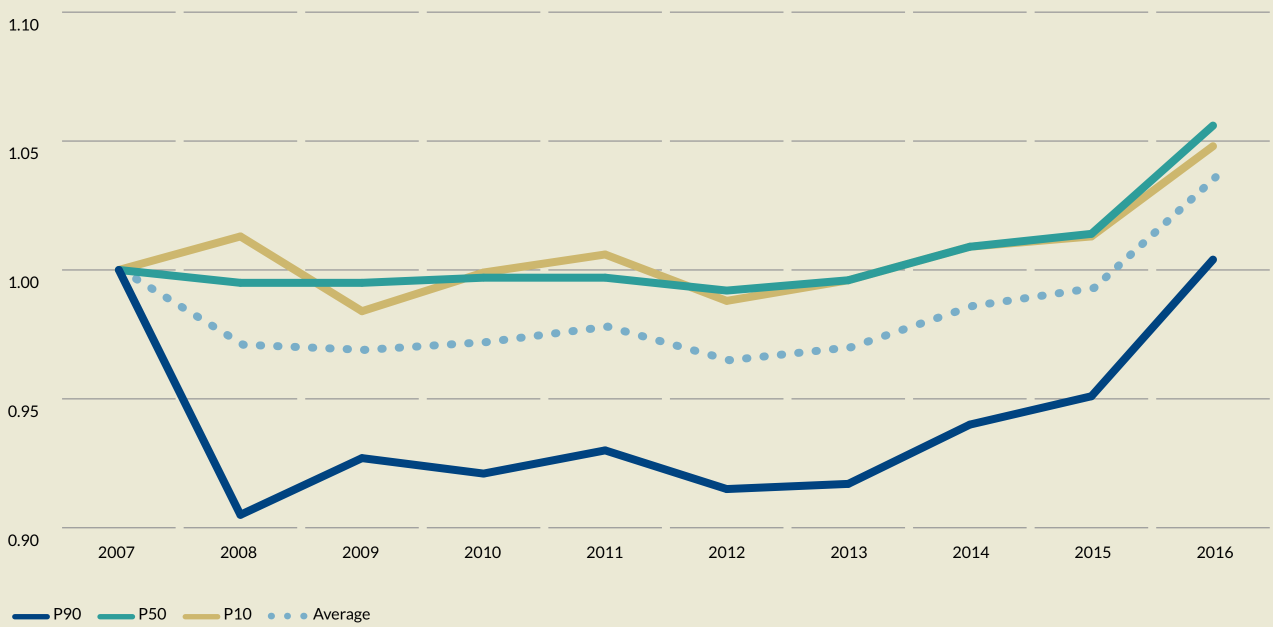
FIGURE 6: **Cumulative Changes of Price Markups Across the Distribution**




This figure presents the time paths of different moments of the distribution of revenue-weighted average price markups (2007=1) for manufacturing, trade, and services. We plot the 10th (yellow), 50th (green), and 90th percentiles (blue) of the revenue-weighted firm-level markups over time, calculating the respective percentiles on an annual basis and thus allowing firms to move within the distribution given their respective markup ranking. For more estimation details, see the notes for Figure 1.
Source: Authors' own calculations.

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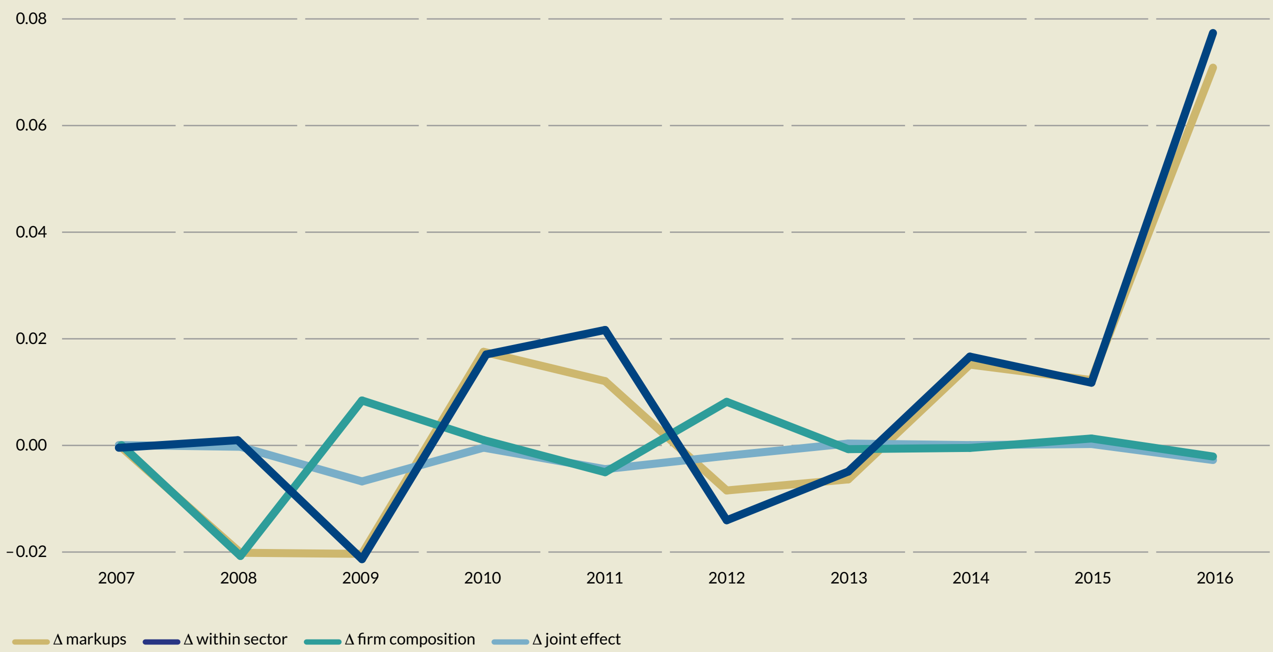
FIGURE 7: **Decomposition of Price Markups**




This figure presents the results of the decomposition exercise (De Loecker et al., 2020) in equation (8) for manufacturing, trade, and services. We plot the change in price markups $\Delta\,\mu_t$ and its three components: the change of markups within a given sector, the markup-relevant change of the composition of a given sector, and a cross-term capturing both of these first two effects. For more estimation details, see the notes for Figure 1.
Source: Authors' own calculations.

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weighted price markups in Figure 6). More specifically, we plot cumulative markup changes for the 10th (lower decile – yellow line), 50th (median – green line), and 90th percentiles (upper decile – blue line) of the firm-level price markup distribution. The figure allows us to explore the different time paths of different parts of that distribution.

We can see that firms at the top of the distribution (blue line) with high markups are also those that experienced a sharper drop during the financial crisis. Their markups level did not return to pre-crisis levels (2007) until 2016. Unlike firms with high markups, firms with lower markups returned to pre-crisis levels around the year 2013.

## 4.4 Decomposition of Price Markups

Are changes in price markups a result of an across-the-board change of markups within an industry? Or does the sector composition change in a way so as to affect average price markups? To answer these questions, we follow the approach in De Loecker et al. (2020) and decompose the change in average price markups, $\Delta\mu_t$, as a function of three components: the change of markups within a given sector, the markup-relevant change of the composition of a given sector, and a cross-term capturing both of these first two effects. Formally, this decomposition is captured by the following formula:

$$(8)\quad \Delta\mu_t = \underbrace{\sum_s \frac{Y_{i,t-1}}{Y_{S,t-1}} \Delta\mu_{st}}_{\Delta\, within} + \underbrace{\sum_s \mu_{s,t-1} \Delta \frac{Y_{it}}{Y_{St}}}_{\Delta composition} + \underbrace{\sum_s \Delta\mu_{st} \Delta \frac{Y_{it}}{Y_{ST}}}_{\Delta cross\text{-}term}$$

with $Y_{st} = \sum_{i \in s} Y_{it}$ the revenue share of sector $S$ over the entire sample. The first component, $\Delta$within, is the change in price markups that is due to a change of the average price markup at a given sector. The second component, $\Delta$composition, is the change in price markups due to the change in the composition of the sector (e.g., when the share of firms with higher price markups increases). The third component, $\Delta$cross-term, captures a joint effect of the former two.

In Figure 7, we plot the results of this composition exercise. The total effect $\Delta\mu_t$ is depicted by the yellow line. The first, second, and third components are depicted by the dark blue, and light blue lines, respectively. We can see that both the sector *composition* (green line) and the *joint effect* (light blue line) have a minor influence on the change in average markups. The primary factor of $\Delta\mu_t$ are changes in markups within a given sector (dark blue line). This means that, for our sample of Germany, increases in price markups are driven by increases of markups across *all* firms – some firms disproportionately outperforming others in terms of price markups (e.g., "superstar firms" as in Autor et al. (2020)) does not seem to play an important role.

## 4.5 Competition and Exposure to Competition

Price markups at the firm level capture a firm's ability to raise price above marginal cost. More pricing power (i.e., market power) implies that a firm is less constrained by competitive forces within its market. As such, price markups are a measure for the degree of a firm's exposure to competition. In Table 6, we show regression results that establish a link between the firm-level exposure to competition (through a firm $i$ estimated markup) and industry-level competition (proxied by the industry's *leave-one-out mean* of price markups).[30] We explore if a decrease in industry-level competition is associated with a decrease in a given firm's exposure to competition (that is, a higher price markup).

In columns (1) and (3) of the table, we report the results for industry averages calculated at the 2-digit Nace level (divisions) and 3-digit Nace level (classes), respectively. In columns (2) and (4), we report results for industry averages (as explanatory variables) at the respective Nace levels and for the federal state *(Bundesland)* that firm $i$ is located in. In a U.S. context, Rossi-Hansberg et al. (2020) argue that regional concentration ratios are more meaningful for the prevailing market structures than nationwide ratios, as most product markets have to be defined regionally. To account for potential prevalence of regional (rather than national) competition for this exercise, we construct average markups at the *Bundesland* level in columns (2) and (4).

For manufacturing and trade, we find positive associations between industry-level markups and a given firm's markup, supporting the idea that firm-level and industry-level measures of competition move hand-in-hand. Note, however, that elasticities are - across the board – less than unity. An increase in industry average markups ("competition") does not one-to-one translate into higher firm-level markups („exposure to competition" or "market power").

30 Industry's leave-one-out average means that the industry average associated with firm $i$ is calculated using all but firm $i$'s observation:
$$leave-one-out\ mean_{it} = \sum_{j \neq i} \frac{Y_{jt}}{\sum_k Y_{kt}} \mu_{jt} \sum_{j \neq i} s_{jt} \mu_{jt},$$
with $Y_{it}$ firm $i$'s revenue in $t$.

TABLE 6: **Firm-Level Markups vs. Industry Averages**

| | 2-Digit Nace | | | | 3-Digit Nace | | | |
|---|---|---|---|---|---|---|---|---|
| | Industry | | Industry x Bundesland | | Industry | | Industry x Bundesland | |
| Dependent variable: ln (Markup$_{it}$) | (1) | | (2) | | (3) | | (4) | |
| **Panel (a):** All Sectors | | | | | | | | |
| ln (Average markup$_t$) | 0.2330*** | (0.0320) | 0.0561*** | (0.00634) | 0.1240*** | (0.0154) | 0.0428*** | (0.00786) |
| Observations | 56,884 | | 55,568 | | 56,894 | | 56,850 | |
| Firms | 11,298 | | 11,080 | | 11,302 | | 11,298 | |
| Adj. $R^2$ | 0.084 | | 0.072 | | 0.064 | | 0.062 | |
| **Panel (b):** Manufacturing | | | | | | | | |
| ln (Average markup$_t$) | 0.4940*** | (0.0591) | 0.0602*** | (0.00606) | 0.6150*** | (0.0409) | 0.0747*** | (0.0136) |
| Observations | 26,636 | | 26,059 | | 26,637 | | 26,610 | |
| Firms | 5,148 | | 5,065 | | 5,149 | | 5,144 | |
| Adj. $R^2$ | 0.212 | | 0.160 | | 0.161 | | 0.149 | |
| **Panel (c):** Trade | | | | | | | | |
| ln (Average markup$_t$) | 0.6900*** | (0.0597) | 0.0548*** | (0.0126) | 0.8750*** | (0.122) | 0.0742*** | (0.0188) |
| Observations | 17,582 | | 17,565 | | 17,582 | | 17,579 | |
| Firms | 3,484 | | 3,479 | | 3,484 | | 3,484 | |
| Adj. $R^2$ | 0.069 | | 0.054 | | 0.065 | | 0.054 | |
| **Panel (d):** Services | | | | | | | | |
| ln (Average markup$_t$) | 0.1320*** | (0.0273) | 0.0513*** | (0.0101) | 0.0197 | (0.0262) | 0.0225* | (0.0115) |
| Observations | 12,678 | | 11,912 | | 12,679 | | 12,644 | |
| Firms | 2,710 | | 2,571 | | 2,710 | | 2,704 | |
| Adj. $R^2$ | 0.084 | | 0.082 | | 0.074 | | 0.074 | |

The table reports (unbalanced) panel fixed effects regression results with the natural log of firm i's markup as dependent variable and log of industry average markup as explanatory variables. Further controls (not reported) include log of firm i's assets, firm and year fixed effects. Industry average for price markups are at the 2-digit Nace level (column (1)), at the 2-digit Nace x federal state (Bundesland) level (column (2)), at the 3-digit Nace level (column (3)), and at the 3-digit Nace x federal state (Bundesland) level (column (4)). Industry averages are leave-one-out means: the industry average associated with firm i is calculated using all but firm i's observation. We report regression results for the subsample of firms in manufacturing, trade, and services. For more estimation details, see the notes for Figure 1. Robust standard errors in parentheses.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Souce: Authors' own calculations.

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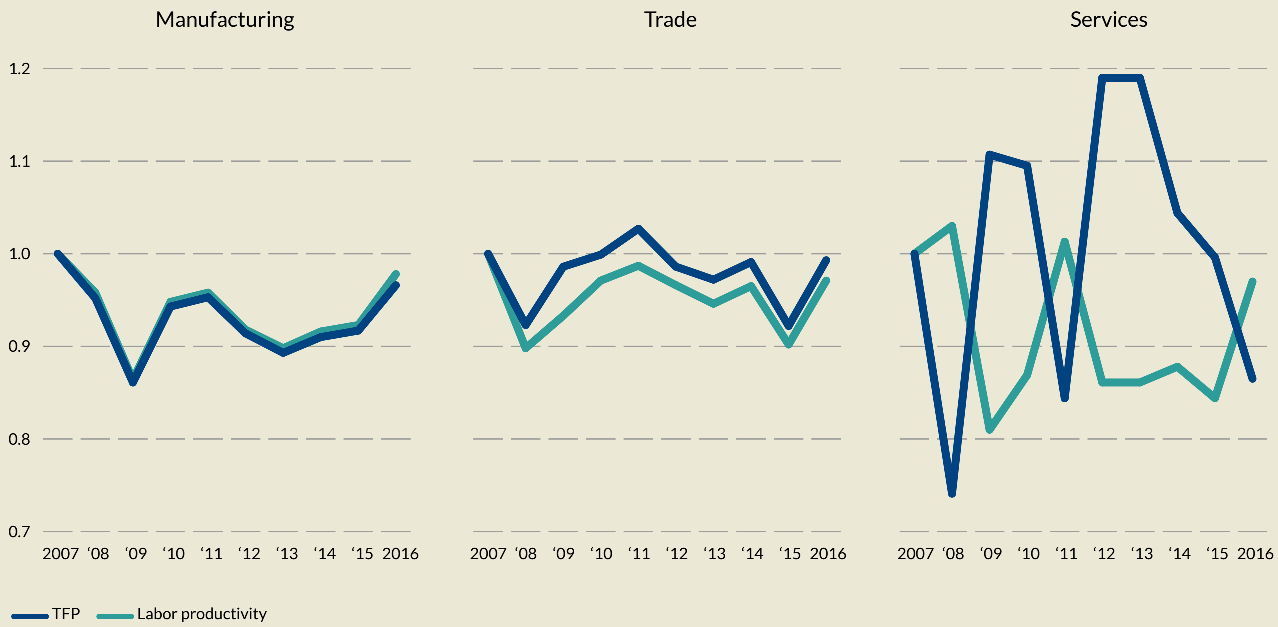
We also find stronger associations when industry averages are calculated at the national level (in columns (1) and (3)) rather than at the federal-state level (in columns (2) and (4)). These findings suggest that (for our estimation sample), defining product markets at the regional level is not as relevant as argued, e. g., for the U.S. by Rossi-Hansberg et al. (2020).

## 4.6 Productivity Measures

For our main results (in the next Section 5), we use two productivity measures: total factor productivity and labor productivity. In Figure 8, we plot time series of these two measures separately for each industry. Total factor productivity (TFP) is depicted by the blue line; labor productivity is depicted by the green line. We normalize both series with

FIGURE 8: **Productivity Estimates by Sector (Nace Section)**




This figure presents the time series for the (revenue-weighted) averages of the two productivity measures used in this report: total factor productivity – TFP (blue line) and labor productivity (green line). Data is for manufacturing, trade, and services.
For an introduction of both measures, see Section 2.2. Values are normalized (within each sector), with the values for 2007 equal to 1.
For the calculation of means, productivity measures are winsorized (bottom and top percentile).
Source: Authors' own calculations.

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the year 2007 as the base year (and values equal to 1). As for depiction of average price markups in the previous section, we present revenue-weighted productivity measures:

$$(9)\quad Average\ productivity_t = \sum_i \frac{Y_{it}}{\sum_j Y_{jt}} \cdot Productiviy_{it}$$

where $Y_{it}$ is firm $i$'s revenue in $t$ so that the fractional expression captures a firm's revenue-based market share.

For both manufacturing and trade we see a close relationship between total factor productivity and labor productivity. For services, on the other hand, the two time series exhibit substantial differences. Overall, our firm-level productivity measures are highly correlated with a correlation coefficient of 0.77 (reported in Table 7). Figure 8 furthermore confirms a long-run slowdown for both productivity measures in all three sectors over the period 2007 to 2016. In all three sectors the normalized value of productivity in 2016 is below 1, implying a decline in productivity compared to 2007. In manufacturing and trade it has only been in the very recent years that productivity rises again though it is still below the 2007 value. While labor productivity has been fairly stable over the period in services, it is much more volatile for TFP, and furthermore TFP shows a declining trend in services since 2013 as well.

# 5 Baseline Relationship between Price Markups and Productivity

In this section, we present results on the baseline relationship between productivity and markups. We refer to these results as "baseline" as they do not yet explore underlying mechanisms. The reported effects represent a *combined* effect of markups on productivity. The results are based on our full estimation sample for manufacturing, trade, and services. In Section 6 below, we will add innovation to the picture to show if this combined effect stems from, e.g., managerial incentives that may be weaker for firms that face less competitive pressure *(direct effect)* or arises by way of innovation *(indirect effect)*.

We address the question from a number of different angles. In Section 5.1, we first explore the relationship between price markups and productivity in a static sense – showing both descriptive evidence and results from a simple regression analysis where we juxtapose today's productivity and today's price markups. The result from this first step should be interpreted as the correlation between markups and productivity but not as a causal link from markups to productivity. The key concern against a causal interpretation of the results in this first step is reverse causality. That is, it might be that we find a correlation between the two variables not because markups affect productivity but because productivity affects markups. In order to alleviate this endogeneity concern, we examine the intertemporal link between markups and productivity in Section 5.2, presuming that lagged price markups are a determinant of firm-level productivity. Ideally, this second step allows us to draw *causal* conclusions on the effect of markup on productivity.

## 5.1 Price Markups and Productivity: Simple Associations

### 5.1.1 Descriptive Evidence

Simple linear correlation coefficients, such as those reported in Table 7, suggest a negative relationship between productivity and price markups. For the total economy (manufacturing, trade, and services), the coefficient for price markups and labor productivity is −0.2, the coefficient for price markups and total factor productivity is −0.31. The correlations are strongest for firms in the trade sec-

TABLE 7: **Pairwise Correlations**

| | Markup | Labor Productivity |
|---|---|---|
| **Panel (a):** Total Economy | | |
| Labor Productivity | −0.198*** | |
| Total Factor Productivity | −0.313*** | 0.766*** |
| **Panel (b):** Manufacturing | | |
| Labor Productivity | −0.425*** | |
| Total Factor Productivity | −0.437*** | 0.998*** |
| **Panel (c):** Trade | | |
| Labor Productivity | −0.619*** | |
| Total Factor Productivity | −0.600*** | 0.977*** |
| **Panel (d):** Services | | |
| Labor Productivity | 0.229*** | |
| Total Factor Productivity | −0.231*** | 0.413*** |

This table reports Pearson correlation coefficients for firm-level price markups and the two productivity measures (both in natural logarithm scale) for the total economy (manufacturing, trade, and services) and separately for each of the sectors. *** indicates statistical significance (different from 0) at the 1 percent level.
Souce: Authors' own calculations.

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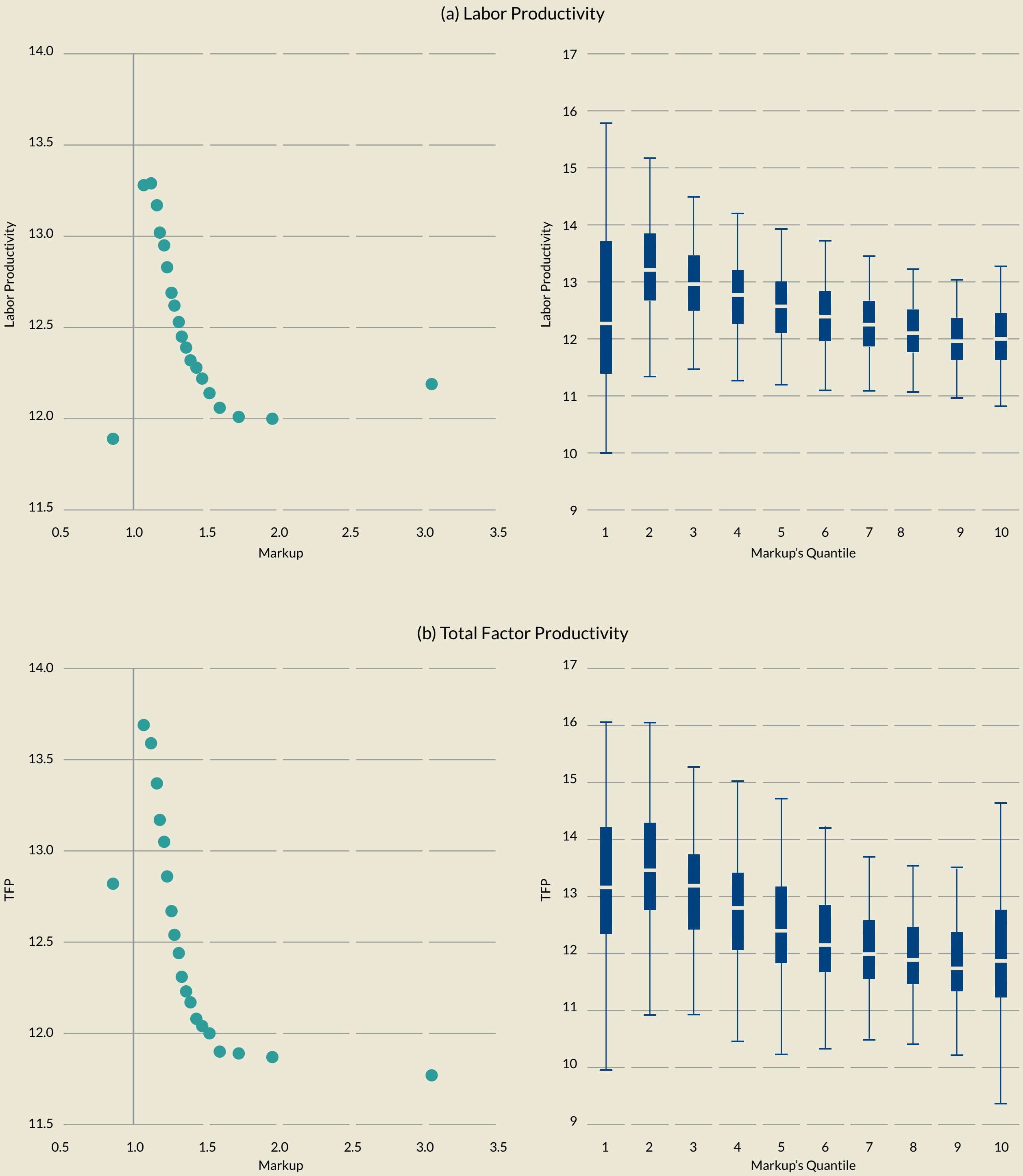
FIGURE 9: **Productivity and Price Markups**




This figure offers a visualization of the negative correlation coefficients presented in Table 7. In panel (a) on the top, we present data for labor productivity; in panel (b) on the bottom, we present data for total factor productivity. Data are for manufacturing, trade, and services (total economy). The figures on the left present scatter plots of the average productivity for different values of price markups (in bins of ascending value). The figures on the right provide box plots of the productivity distribution for each markup decile.
Source: Authors' own calculations.

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tor (−0.62 and −0.60) and weakest in services. In fact, for firms in services, price markups and labor productivity exhibit a positive correlation whereas price markups and total factor productivity exhibit a negative correlation. We will explore these patterns in greater detail further below.

In Figure 9, we explore the relationship graphically for labor productivity (top panel) and total factor productivity (bottom panel). The two graphs on the left of Figure 9 plots the average productivity for a given bin of price markups. Except for price markups with values less than 1 (meaning that prices are below cost; depicted by vertical lines) and sufficiently high values (i. e., markup values above 2, so that markups are 100 percent and higher), we find that higher markups are associated with lower average productivity. We also observe a higher variance for the lowest markup deciles (and for total factor productivity also the highest decile), as can be seen in the box plots of the productivity distribution for each price markup decile in the figures on the right. This means that for firms with price markups that are not in the tails of their distributions, the negative relationship between markups and productivity is robust.

### 5.1.2 Evidence from Regression Models

The positive correlation between markups and productivity seen in the descriptive analysis might be driven by other underlying factors such as industry or time. We therefore employ multivariate regression analyses that allow us to control for other factors that might affect firm-level productivity. The goal is to make *ceteris-paribus* statements: all else equal, how are price markups associated with productivity? We begin with a simple static analysis, exploring the contemporaneous relationship between productivity of a given firm in a given period and the degree of competition (proxied by price markups) that firm faces in that same period. To this end, we estimate the following empirical model:

(10) $ln\,(Productivity_{it}) = f\,(ln(Markup_{it}), \cdot).$

It states that productivity is a function of price markups as well as other factors, represented by $(\cdot)$. For our empirical results, we control for year and industry effects to capture time and industry variation in productivity that is not associated with price markups. For the convenient interpretation of our estimated coefficients as elasticities, we use both productivity and markup measures in logarithmic scale. The interpretation of our estimation coefficients as elasticities implies statements of the type: *"an increase of price markups by 1 percent is associated with an increase/decrease of productivity by x percent."* It is important to keep in mind that, with the above specification, we do not yet make any causal statements.

In Table 8, we present the estimation results for the model in equation (10). Columns (1) and (3) contain results for pooled OLS estimations, adding dummies for 2-digit Nace codes (divisions) and year to control for variation across industries and time. Columns (2) and (4) contain results for unbalanced panel fixed-effects estimations. We report results for the sectors manufacturing in panel (b), trade in panel (c), and services in panel (d). In panel (a), we report results for all three sectors combined.

Our estimation results show a negative relationship between price markups and firm-level productivity, confirming our descriptive analysis from above.[31] When considering the data for the total economy (i. e., manufacturing, trade, and services), a 1 percent increase in price markups is associated with a 1.3 percent (pooled OLS specification) to 0.2 percent (panel specification) *decrease* in productivity. These results are statistically significant and robust for both productivity measures. We observe some variation of these results across sectors. In both manufacturing and trade the relationship between markups and productivity is negative, with elasticities of -2.2 and -4.2 for the pooled OLS specification and -0.8 and -2.3 for the panel specification. The results imply that, after controlling for industry and time variation, we still find that *more competition (at a given point in time) is associated with higher productivity at that time.*

The robust negative association observed for firms in manufacturing and trade does not carry over to firms in the service sector. As we show in panel (d) of Table 8, markups and productivity exhibit a positive association in most of our specifications. The structural differences between manufacturing and trade on the one hand and services on the other hand, observed for linear correlations in Table 7 are present even after controlling for industry and time variation.

Price markups explain firm-level productivity to varying degrees across sectors. For firms in manufacturing, the firm-level variation in markups explains about 20 percent

31 As we report in Table 18 in the appendix, the estimated elasticities are constant over time. The interaction terms with year dummies are statistically insignificant except for manufacturing in the years 2015 and 2016 (implying a weaker negative association relative to earlier years).

TABLE 8: **Regression Results (Associations)**

| Dependent variable: $\ln(\text{Productivity}_{it})$ | Labor Productivity: Pooled OLS (1) | Labor Productivity: Panel FE (2) | TFP: Pooled OLS (3) | TFP: Panel FE (4) |
|---|---|---|---|---|
| **Panel (a):** Total Economy (Observations: 56,894; Firms: 11,302) | | | | |
| $\ln(\text{Markup}_{it})$ | −1.276*** (0.0452) | −0.232*** (0.0402) | −1.425*** (0.0464) | −0.271*** (0.0405) |
| Adj. $R^2$ / $R^2_{within}$ | 0.359 | 0.038 | 0.600 | 0.038 |
| Adj. $R^2$ (markups only) | 0.097 | | 0.153 | |
| **Panel (b):** Manufacturing (Observations: 26,637; Firms: 5,149) | | | | |
| $\ln(\text{Markup}_{it})$ | −2.187*** (0.0632) | −0.766*** (0.0609) | −2.225*** (0.0617) | −0.802*** (0.0604) |
| Adj. $R^2$ / $R^2_{within}$ | 0.329 | 0.120 | 0.334 | 0.124 |
| Adj. $R^2$ (markups only) | 0.193 | | 0.203 | |
| **Panel (c):** Trade (Observations: 17,582; Firms: 3,484) | | | | |
| $\ln(\text{Markup}_{it})$ | −3.930*** (0.0965) | −2.064*** (0.1380) | −4.198*** (0.1140) | −2.294*** (0.1560) |
| Adj. $R^2$ / $R^2_{within}$ | 0.503 | 0.227 | 0.480 | 0.227 |
| Adj. $R^2$ (markups only) | 0.425 | | 0.402 | |
| **Panel (d):** Services (Observations: 12,679; Firms: 2,710) | | | | |
| $\ln(\text{Markup}_{it})$ | 0.153*** (0.0399) | 0.401*** (0.0381) | −0.047 (0.0400) | 0.360*** (0.0343) |
| Adj. $R^2$ / $R^2_{within}$ | 0.255 | 0.134 | 0.810 | 0.126 |
| Adj. $R^2$ (markups only) | 0.073 | | 0.062 | |
| Year FE | Yes | Yes | Yes | Yes |
| 2-digit Industry FE | Yes | No | No | No |
| Firm FE | No | Yes | No | Yes |

The table reports results from pooled OLS and unbalanced panel fixed-effects regressions. Dependent variable is the natural logarithm of productivity (either labor productivity or total factor productivity, where the latter is obtained from the production-function estimation in log scale). Independent variable of interest is the natural logarithm of firm-level price markups. Reported coefficients are interpreted as elasticities. Year and industry dummy variables are added as additional control variable in all specifications (as indicated). We report regression results for the total economy (manufacturing, trade, and services) in panel (a) and separately for the three subsamples in panels (b)-(d). Manufacturing (1-digit Nace code C) comprises 2-digit Nace codes 10-33, trade (G) comprises Nace codes 45-47 and "services"-related sections comprise Logistics (H: 49-53), Accommodation & food services (I: 55-56), IT (J: 58-63), Real estate (L: 68), Professional (M: 69-75), and Administration (N: 77-82). For more markup estimation details, see the notes for Figure 1. Robust standard errors in parentheses. For OLS: standard errors clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Souce: Authors' own calculations.

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of the variation in productivity.[32] Price markups exhibit a significantly higher explanatory power in trade, where this figure exceeds 40 percent. Following Cohen (1988), the effect size for manufacturing and trade is considered *large*. In services, on the other hand, the effect of price markups in explaining productivity is of *medium* size. The percentage of the variation in firm-level productivity that is attributable to price markups is at 6 percent to 7 percent.

Overall, when averaging over the total economy (panel (a) of the table), the variation in price markups explains about 10 percent to 15 percent of the variation of firm-level productivity (a medium to large effect size).[33]

32 See the reported numbers for "Adj. $R^2$ (markups only)." These are the $R^2$ numbers from pooled OLS models with $\ln(\text{Markup}_{it})$ as the only explanatory variable.

33 The effect size is determined by *Cohen's f*, which is equal $\sqrt{R^2/1-R^2}$ to where $R^2$ is the value for "Adj. $R^2$ (markups only)" from the regression table (Cohen, 1992). Effect sizes (i.e., values off *f*) of 0.1, 0.25, and 0.40 are considered small, medium, and large, respectively (Cohen, 1988).

TABLE 9: **Regression Results (Intertemporal Relationship)**

| Dependent variable: ln($Productivity_{it}$) | Labor Productivity (1) | | TFP (2) | | Labor Productivity (3) | | TFP (4) | |
|---|---|---|---|---|---|---|---|---|
| **Panel (a):** Total Economy (Observations: 45,428 / 36,489) | | | | | | | | |
| ln (Average $markup_{i,t-1}$) | – 1.320*** | (0.0500) | – 1.468*** | (0.0518) | | | | |
| ln(Average $markup_{i,t-2}$) | | | | | – 1.341*** | (0.0542) | – 1.493*** | (0.0564) |
| Adj. $R^2$ | 0.361 | | 0.597 | | 0.359 | | 0.590 | |
| Adj. $R^2$ (markups only) | 0.097 | | 0.151 | | 0.094 | | 0.148 | |
| **Panel (b):** Manufacturing (Observations: 21,340 / 17,229) | | | | | | | | |
| ln (Average $markup_{i,t-1}$) | – 2.148*** | (0.0679) | – 2.186*** | (0.0663) | | | | |
| ln (Average $markup_{i,t-2}$) | | | | | – 2.100*** | (0.0734) | – 2.140*** | (0.0718) |
| Adj. $R^2$ | 0.321 | | 0.325 | | 0.308 | | 0.312 | |
| Adj. $R^2$ (markups only) | 0.178 | | 0.188 | | 0.167 | | 0.178 | |
| **Panel (c):** Trade (Observations: 14,031 / 11,297) | | | | | | | | |
| ln (Average $markup_{i,t-1}$) | – 3.933*** | (0.108) | – 4.217*** | (0.129) | | | | |
| ln (Average $markup_{i,t-2}$) | | | | | – 3.903*** | (0.116) | – 4.198*** | (0.138) |
| Adj. $R^2$ | 0.485 | | 0.450 | | 0.472 | | 0.453 | |
| Adj. $R^2$ (markups only) | 0.405 | | 0.385 | | 0.389 | | 0.371 | |
| **Panel (d):** Services (Observations: 9,921 / 7,833) | | | | | | | | |
| ln (Average $markup_{i,t-1}$) | 0.1210*** | (0.0438) | – 0.0747* | (0.0442) | | | | |
| ln (Average $markup_{i,t-2}$) | | | | | 0.1120** | (0.0473) | – 0.0884* | (0.0478) |
| Adj. $R^2$ | 0.255 | | 0.816 | | 0.256 | | 0.816 | |
| Adj. $R^2$ (markups only) | 0.073 | | 0.068 | | 0.074 | | 0.070 | |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| 2-digit Industry FE | Yes | | Yes | | Yes | | Yes | |

The table reports results from pooled OLS regressions with year and industry FE. Dependent variable is the natural logarithm of productivity. Independent variable of interest is the natural logarithm of the once and twice lagged firm-level price markups (ln($Markup_{i,t-1}$) and ln($Markup_{i,t-2}$)). Reported coefficients are interpreted as elasticities.
Year and industry dummy variables are added as additional control variable in all specifications. For more markup estimation details, see the notes for Figure 1. For more details on the regression sample, see the notes for Table 8. Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.
Souce: Authors' own calculations.

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To summarize our first set of results, we find that for manufacturing and trade, more competition is positively associated with higher productivity (assuming that higher markups imply less competition). This relationship is reversed in the services sector. Moreover, the role that price markups play in explaining the firm-level variation is strongest in trade and weakest in services.

## 5.2 Price Markups and Productivity: Intertemporal Relationship

The estimated model in equation (10) and the respective results in Table 8 do not allow for any causal interpretation in a sense that markups determine productivity. The reported associations are potentially subject to a reverse-causality problem. This means, while we estimate productivity as a function of markups (and other factors), presuming that markups determining productivity, the true relationship could reversed and productivity determines markups.[34]

To address concerns of reverse causality, we estimate the model in equation (10) using once/twice lagged price markups as our explanatory variable of interest. This yields the following estimation specification:

$$\ln(Productivity_{it}) = f(\ln(Markup_{i,t-\tau}), \cdot) \quad \tau = 1,2 \tag{11}$$

The value $\tau=1$ means that we estimate this year's productivity as a function of last year's price markups. Similarly, with $\tau=2$, we postulate that price markups affect productivity with a two-year delay. Given these time lags, reverse causality is no longer of concern and under certain assumptions the estimated coefficients identify the causal effect of lagged markups on productivity.[35] We use again both productivity and markup measures in logarithmic scale and interpret our estimated coefficients as elasticities, allowing for statements of the type: *"an increase of price markups by 1 percent lead to an increase/decrease of next year's productivity by x percent."*

We present results from pooled OLS regressions in Table 9.[36] Our earlier findings in Table 8 for simple associations continue to hold. We find a significantly negative relationship between price markups and firm-level productivity. With the lagged time structure in the specification in equation (11), however, we can now conclude that price markups have a negative *effect* on productivity. For the total economy (manufacturing, trade, and services combined), a 1 percent increase in price markups lowers productivity by 1.3 percent (labor productivity) to 1.5 percent (TFP). The effects do not vary greatly with the time lag. In fact, the estimated elasticities in Table 9 (in columns (1) and (2) for markups in $t-1$ and columns (3) and (4) for markups in $t-2$) are very close in magnitude to the elasticities reported in Table 8 (in columns (1) and (3)). Moreover, price markups in $t-1$ (and $t-2$) explain similar percentages of the variation in firm-level productivity.

Our findings suggest that pro-competitive policies (with the effect of curbing firm's market power and lowering firm-level price markups) have the potential to increase firm-level productivity. This policy implication applies to both the manufacturing and trade sector for which we find a negative effect of price markups on productivity. As with the earlier results reported in Table 8, the situation is different when considering services. When using labor productivity, we find a *positive* effect of price markups on productivity. The effect is small (a 1 percent increase in price markups increases productivity by 0.1 %) but precisely estimated. When using TFP as the productivity measure, the effect is negative and statistically significant (at the 10 % level), but even smaller in magnitude.

The estimated effects of price markups on productivity are *combined* effects and represent our baseline results. They are as such not indicative of any underlying mechanisms. To explore these mechanisms, in the next section, we add a firm's innovation activity to the equation to disentangle the combined effects and separately estimate a direct effect (taking available technology as given) and an indirect effect (by endogenizing a firm's innovation activity).

34 In fact, other authors have estimated such a reversed relationship, explaining markups as a function of productivity (e.g. Altomonte et al., 2018).

35 The key assumption is that the error term in equation (11) is not correlated over time (no autocorrelation).

36 Because we estimate our main models with innovation in the next section using pooled OLS specifications, we restrict attention to this estimation strategy in this table.

# 6 The Role of Innovation

The literature has discussed two key explanations of a positive effect of competition on productivity. On the one hand, more competition may give rise to managerial practices that employ the firm's resources more efficiently ("quiet-life hypothesis" (Hicks, 1935) or the notion of "X-inefficiency" (Leibenstein, 1966)).[37] Competition is said to have a *direct* effect on productivity. This explanation takes the firm's access to technology (and the technological status quo) as given. The second explanation endogenizes the available technology: higher competition may create incentives for the firm to innovate, and more innovation in return is said to have a positive effect on productivity (Hall, 2011; Mohnen and Hall, 2013; Peters et al., 2017). Following this second explanation, competition has an additional *indirect* effect on productivity. In this section, we disentangle the combined effect presented in Table 9 to explore the relative importance of the direct and indirect effect.

## 6.1 Innovation Data

### 6.1.1 Mannheim Innovation Panel

In order to investigate the indirect effect markups might have on productivity via innovation, we use the Mannheim Innovation Panel (MIP) as the second main data source. The MIP is an annual representative survey that collects information about firm's innovation activities. The survey methodology and definitions of innovation indicators follows the Oslo manual on innovation surveys (OECD and Eurostat, 2019), thereby yielding internationally comparable innovation data. The MIP has been conducted by the ZEW – Leibniz Centre for European Economic Research, in cooperation with the Fraunhofer Institute for Systems and Innovation Research (ISI) and the Institute for Applied Social Sciences (infas), on behalf of the German Federal Ministry of Education and Research (BMBF) since 1993.

The target population spans all legally independent firms with five or more employees and their headquarters located in Germany. A firm is defined as the smallest combination of legal units operating as an organizational unit producing goods or services. The MIP is a random stratified sample, stratified by eight size classes, two regions (East and West Germany) and 56 Nace 2-digit industries. The industries covered by the MIP include manufacturing, mining, energy and water supply, construction, trade and services. As for our estimation of price markups, we restrict the sample to manufacturing, trade, and services. The MIP is furthermore designed as a panel; that means, it allows tracking firms over time. However, since participation is voluntary, the panel is unbalanced. Every second year the MIP represents the German contribution to the Europe-wide harmonized Community Innovation Surveys (CIS) under the coordination of Eurostat.

### 6.1.2 Matched Orbis-MIP Sample

MIP data and Orbis data (as used in our markup estimations) can be matched via the Bureau van Dijk identification number (BvDID). For the period 2007-2016, we merge 6,776 firm-year observations. For these observations, we have information whether firms have introduced product or process innovations. For a smaller subset of firms, we additionally have information on innovation expenditure and R&D expenditure. We describe our innovation variables below.

Comparing the matched sample with the non-matched Orbis sample, we find that the matched sample contains on average lager firms but with lower productivity, both in terms of labor productivity and TFP. However, the two samples do not significantly differ at the 5 percent level in price markups. We report the mean value for these key variables in the matched Orbis-MIP sample and the non-matched (full) Orbis estimation sample in Table 10.

37 For recent empirical results, see Schmitz (2005), Matsa (2011), Bloom et al. (2019), or Backus (2019).

TABLE 10: **Characteristics of Matched Sample**

| Variable | Matched Orbis-MIP Sample | Non-Matched Orbis Sample | Mean Diff Test (p-value) |
|---|---|---|---|
| ln (Employees) | 5.622 | 5.024 | 0.000 *** |
| ln (Labor Productivity) | 12.316 | 12.572 | 0.000 *** |
| ln (TFP) | 12.206 | 12.592 | 0.000 *** |
| ln (Markup) | 0.318 | 0.313 | 0.145 |

The table reports means of key variables (natural logarithms of employees as an indicator for firm size, labor productivity, total factor productivity TFP, and price markups) for the matched Orbis-MIP sample and the non matched (full) Orbis estimation sample. Both samples contain data for manufacturing, trade, and services. The mean values of ln (employees) correspond to an average number of employees of about 276.3 in the matched sample and 152.0 in the non-matched Orbis sample. *** $p < 0.01$
Souce: Authors' own calculations.

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TABLE 11: **Regression Results (Intertemporal) for Matched Orbis-MIP Sample**

| Dependent variable: $\ln(\text{Productivity}_{it})$ | Labor Productivity (1) | | TFP (2) | | Labor Productivity (3) | | TFP (4) | |
|---|---|---|---|---|---|---|---|---|
| **Panel (a):** Total Economy (Observations: 6,532 / 5,369; Firms: 1,962/1,699) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-1})$ | – 0.463*** | (0.095) | – 0.680*** | (0.093) | | | | |
| $\ln(\text{Markup}_{i,t-2})$ | | | | | – 0.468*** | (0.105) | – 0.697*** | (0.102) |
| **Panel (b):** Manufacturing (Observations: 4,385 / 3,617; Firms: 1,301/1,135) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-1})$ | – 1.910*** | (0.175) | – 1.940*** | (0.175) | | | | |
| $\ln(\text{Markup}_{i,t-2})$ | | | | | – 1.834*** | (0.193) | – 1.856*** | (0.194) |
| Adj. $R^2$ | 0.327 | | 0.332 | | 0.312 | | 0.316 | |
| **Panel (c):** Trade (Observations: 652 / 528; Firms: 207/180) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-1})$ | – 3.589*** | (0.374) | – 3.552*** | (0.440) | | | | |
| $\ln(\text{Markup}_{i,t-2})$ | | | | | – 3.681*** | (0.393) | – 3.622*** | (0.455) |
| Adj. $R^2$ | 0.453 | | 0.409 | | 0.457 | | 0.406 | |
| **Panel (d):** Services (Observations: 1,495 / 1,224; Firms: 454/384) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-1})$ | 0.357*** | (0.081) | 0.057 | (0.103) | | | | |
| $\ln(\text{Markup}_{i,t-2})$ | | | | | 0.365*** | (0.091) | 0.037 | (0.108) |
| Adj. $R^2$ | 0.349 | | 0.780 | | 0.347 | | 0.782 | |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| 2-digit Industry FE | Yes | | Yes | | Yes | | Yes | |

The table reports results from pooled OLS panel regressions for the matched sample of ZEW's MIP and Bureau van Dijk's Orbis database. Dependent variable is the natural logarithm of productivity. Independent variable of interest is the natural logarithm of the once and twice lagged firm-level price markups ($\ln(\text{Markup}_{i,t-1})$ and $\ln(\text{Markup}_{i,t-2})$). Reported coefficients are interpreted as elasticities. For more estimation details, see the notes for Table 8. Note that Nace section Accommodation & food services (I: 55-56) is not covered by MIP data and therefore dropped from the matched sample. Standard errors clustered at the firm level. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Souce: Authors' own calculations.

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TABLE 12: **Innovation Variables**

| Variable | Obs. | Mean | Std. dev. | Min | Max |
|---|---|---|---|---|---|
| R&D (0/1) | 3,642 | 0.501 | 0.500 | 0.000 | 1.000 |
| ln(R&D $Exp_{it}$) for R&D $Exp_{it}$ > 0[a)] | 1,823 | 14.183 | 2.301 | 6.908 | 19.743 |
| ln(R&D $Exp_{it}$) for R&D$Exp_{it}$ > 0, 0 o.w.[b)] | 3,642 | 7.099 | 7.277 | 0.000 | 19.743 |
| ln(R&D Expit+1) [c)] | 3,642 | 9.400 | 5.059 | 4.605 | 19.743 |
| Innovation (0/1) | 3,784 | 0.620 | 0.485 | 0.000 | 1.000 |
| ln($InnoExp_{it}$) for $InnoExp_{it}$ > 0 | 2,347 | 14.707 | 2.193 | 6.908 | 20.093 |
| ln($InnoExp_{it}$) for $InnoExp_{it}$ > 0, 0 o.w. | 3,784 | 9.122 | 7.344 | 0.000 | 20.093 |
| ln($InnoExp_{it}$+1) | 3,784 | 10.871 | 5.198 | 4.605 | 20.093 |
| $Product_{it}$ (0/1) | 6,776 | 0.625 | 0.484 | 0.000 | 1.000 |
| $Process_{it}$ (0/1) | 6,766 | 0.568 | 0.495 | 0.000 | 1.000 |

The table reports summary statistics for the innovation variables in the matched Orbis-MIP sample. a) reports log R&D expenditures only for those firms with positive R&D expenditure; b) reports log R&D expenditures for all firms, assuming a value of log R&D of zero for all firms without R&D; c) reports log R&D expenditures for all firms, assuming a value of log (R&D+1) for all firms without R&D. Similarly for innovation expenditure.
Souce: Authors' own calculations.

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## 6.2 Baseline Results with Matched Sample

We re-estimated equation (11) with our matched sample and report the results for the effects of once / twice lagged price markups on firm-level productivity in Table 11. We use markup and productivity estimates based on the full Orbis data. We find that the estimated effects of price markups on productivity in the matched sample are slightly weaker than those found in the full Orbis sample. For manufacturing, the markup-productivity elasticity is approximately -2.2 in the full Orbis sample and -1.9 in the matched sample. For trade, the numbers are -4.2 and -3.6. For services, the estimates for labor productivity are in line with those obtained in Table 9. When total factor productivity is used, the results are insignificant for services in the matched sample.

The results in Table 11 represent the combined effect of price markups on productivity for the matched sample and serve as a benchmark for the remainder of this section.

## 6.3 Productivity and Innovation

For the separation of the direct and indirect effect of markups on productivity, we first explore each step in the two-step mechanism of the indirect effect. The first step is the effect of competition (proxied by price markups) on innovation, the second step is the effect of innovation on productivity.

### 6.3.1 Innovation Variables

For our analysis, we add four key innovation variables from the MIP. We provide summary statistics in Table 12. First, we use the natural logarithm of a firm's R&D expenditure (ln(R&D$Exp_{it}$)). R&D expenditure captures what a firm $i$ spends on intra- and extramural R&D activities in a given year $t$. R&D is creative work undertaken on a systematic basis in order to increase the stock of knowledge and the subsequent use of this stock of knowledge to devise new applications, such as new and improved products and processes. To deal with firms that do not invest in R&D and for which ln(R&D$Exp_{it}$) would not be defined, we follow two approaches. First, we replace ln(R&DExp$it$) by zero for these firms and add a dummy variable to the specification that equals 1 when the firm does not invest in R&D. Alternatively, we add 1 euro to R&D expenditure for each firm. Both approaches gives qualitatively the same results.

TABLE 13: **Effect of Competition on Future Innovation**

| | Total (a) | | Manufacturing (b) | | Trade (c) | | Services (d) | |
|---|---|---|---|---|---|---|---|---|
| **Model (1):** Dep. Var.: $\ln(InnoExp_{it})$ (Observations: 3,149; Firms: 1,278) | | | | | | | | |
| $\ln(Markup_{i,t-1})$ | – 1.706*** | (0.629) | – 3.723** | (1.261) | – 1.010 | (2.360) | – 1.935*** | (0.749) |
| Adj. $R^2$ | 0.307 | | 0.318 | | 0.045 | | 0.318 | |
| **Model (2):** Dep. Var.: $\ln(R\&DExp_{it})$ (Observations: 3,045; Firms: 1,258) | | | | | | | | |
| $\ln(Markup_{i,t-1})$ | – 1.596*** | (0.561) | – 4.140*** | (1.394) | 0.343 | (2.175) | – 1.694*** | (0.613) |
| Adj. $R^2$ | 0.351 | | 0.351 | | 0.011 | | 0.397 | |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| 2-digit Industry FE | Yes | | Yes | | Yes | | Yes | |

The table reports results from pooled OLS panel regressions for the matched sample of ZEW's MIP and Bureau van Dijk's Orbis database. Reported are results for four alternative definitions of innovation. Model (1) and (2) use the natural logarithm of innovation and R&D expenditure, respectively. It is defined as $\ln(R\&D\,Exp_{it} + 1)$ and $\ln(Inno\,Exp_{it} + 1)$ in order to account for zero innovation activity. Coefficients can be interpreted as elasticities. In model (3) and (4), product and process innovation are dummy variables related to the 3-year period t to t – 2. Coefficients divided by 100 can be interpreted as the change in the predicted probability of a firm i introducing a new product or process in response to a 1 percent increase in the firm's price markups. The number of observations / firms refers to the sample for the total economy (manufacturing, trade, and services). Independent variable of interest is the natural logarithm of firm-level price markups in year t – 1. Firm size (proxied by $\ln(Assets_{it})$) is added as an additional control variable. Standard errors are clustered at firm level. * p < 0.1, ** p < 0.05, *** p < 0.01.
Souce: Authors' own calculations.

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Second, instead of using R&D expenditure, we take innovation expenditure of firm in year $t$ to construct ln(InnoExp$it$). The innovation expenditure is the sum of all current expenses for innovation (personnel, material, etc.) as well as investments associated with these innovation activities. Innovation expenditure is a broader concept. In addition to R&D expenditure, it includes outlays for acquisition of external knowledge, machines and equipment, training, market introduction, design, and other preparations for product and/or process innovation activities in a given year. On average, R&D expenditure amounts to 50-60 percent of innovation expenditure.[38] We use the same approaches as for R&D also for firms without innovation expenditure.

Finally, in addition to the input-related expenditure variables, we use two binary output-related indicators $Product_{it}$ and $Process_{it}$ that equal 1 if the firm has introduced a new product (including services) or a new production technology or method of delivery in the three-year period $t$ to $t{-}2$, respectively.

38 A concept even broader than innovation expenditure is *knowledge capital* (Corrado et al., 2005). For a cross-country comparison of knowledge capital in different industries see Belitz and Gornig (2019).

### 6.3.2 Effect of Price Markups on Innovation

In a first step, we examine the effect of price markups on a firm's innovation decision. We estimate the following model:

$$(12)\quad Innovation_{it} = f\,(\ln(Markup_{i,t-1}), \cdot).$$

Innovation in a given period $t$ is a function of price markups in the previous period, among other factors. To account for variation across industries and across time, we include industry and year dummies in our estimation specifications. We also include a measure of firm size to control for size effects.

In Table 13, we report the results of lagged price markups on four different innovation variables. In models (1) and (2), our dependent variables are (the natural logarithm) of a firm's innovation expenditures $(\ln(InnoExp_{it}{+}1))$ and a firm's R&D expenditures $(\ln(R\&DExp_{it}{+}1)$, respectively. The use of natural logarithms allows us to interpret the results as elasticities. In models (3) and (4), the dependent variables are binary variables indicating whether the firm has made product or process innovation in the previous three-year period $t$ to $t{-}2$, respectively. The estimated coefficients (divided by 100) approximately indicate the change in the predicted probability of a firm $i$ introducing a new product or process in response to a 1 percent increase in the firm's price markups. We report our results for the total economy (column (a)) as well as, separately, for manufacturing (b), trade (c), and services (d).[39]

A few interesting patterns emerge. First, the effects of price markups on the innovation and R&D expenditure measures in models (1) and (2) are negative, meaning that more competition has a facilitating effect on innovation (expenditures). For the total economy, our results imply a 1.7 percent and 1.6 percent decrease in innovation and R&D expenditures, respectively, in response to a 1 percent increase in markups. We observe the strongest effect in manufacturing, with elasticities suggesting that a 1 percent increase in price markups decreases innovation and R&D expenditures by 3.7 percent and 4.1 percent, respectively. The effect for services is about half as strong but also significant. For trade, we do not find a statistically significant effect of markups on firms' innovation activities. This might be the result of lower levels of innovation activities in the trade sector (especially with regard to R&D) in combination with the small sample size for that sector.

Second, price markups exhibit a significantly negative effect on firm's decision to introduce a new product (model (3)) but no effect on process innovation (model (4)). The coefficient for the total economy of -0.158 indicate that a 10 percent increase in markups lowers the likelihood of introducing a new product by approximately 0.016 percentage points. Given an overall product innovation rate of 0.625, the size of the effect is rather small. For product innovation, the negative effect of price markups is of similar size for manufacturing and services, but, similar to the expenditure variables, we do not find a statistically significant effect for the trade sector.

Our results add to a long list of articles that have studied the effects of competition on innovation. Recent contributions with results in line with ours are Bloom et al. (2016) (using Chinese imports as a proxy for competition faced by European firms), Aghion et al. (2018) (providing results from laboratory experiments), and Igami and Uetake (forthcoming) (empirically exploiting the consolidation of the hard disk drive industry).

### 6.3.3 Effect of Innovation on Productivity

In a second step, we estimate a model of productivity as a function of lagged price markups and lagged innovation, allowing both variables to co-determine firm-level productivity. The estimated equation is an extension of equation (11), in which we did not explicitly account for innovation as a driver of productivity. The extended model we estimate is as follows:

(13) $ln(Productivity_{it}) = f\,(ln(Markup_{i,t-1}), Innovation_{i,t-1}, \cdot).$

We report results for four different innovation variables and across three different sectors in Table 14. Our dependent variable is total factor productivity. First, we find that innovation has a positive effect on productivity when looking at the expenditure measures (in models (1) and (2)). The estimated elasticities state that a 1 percent increase in either innovation expenditure or R&D expenditure increase productivity by 0.05 percent to 0.08 percent. These estimated effects are statistically significant and well in line with results obtained in the literature, ranging between 0.02 percent and 0.10 percent (Peters et al., 2018). The effect is present for the total economy and manufacturing as well as services (for innovation expenditure).

Our results for product and process innovation dummies are less clear. In contrast to other studies using MIP data (e.g., Peters et al., 2017), we find no significantly positive effect of the introduction of a new product or process on productivity in the manufacturing sector. For services, we find a positive effect for both variables.[40]

As we have already observed in Table 13, there are no innovation-related effects in the trade sector. Innovation expenditure, R&D expenditure, and the process innovation dummy exhibit a statistically insignificant coefficient. The introduction of a new product even has a *negative* effect on firm-level productivity. As discussed earlier, we believe these patterns are the result of lower levels of innovation activities in the trade sector in combination with the small sample size for that sector.

Combining the results from both steps – the effect of markups on innovation as first step and the effect of innovation on productivity as second step – we can conclude that the conjectured *indirect* effect of price markups on productivity by way of innovation is indeed a viable

39 The reported results are from linear probability models. Regression results from probit models show very similar marginal effects.

40 For a comprehensive review of the literature on the effect of innovation and productivity, see Hall (2011) and Mohnen and Hall (2013).

TABLE 14: **Effect of Competition and Innovation on Future TFP**

| Dependent variable: $\ln(TFP_{it})$ | Total (a) | | Manufacturing (b) | | Trade (c) | | Services (d) | |
|---|---|---|---|---|---|---|---|---|
| **Model (1):** Innovation Expenditure (Observations: 2,460; Firms: 918) | | | | | | | | |
| $\ln(Markup_{i,t-1})$ | – 0.801*** | (0.134) | – 2.090*** | (0.179) | – 3.372*** | (0.630) | 0.114 | (0.148) |
| $\ln(InnoExp_{i,t-1})$ | 0.059*** | (0.011) | 0.061*** | (0.011) | – 0.021 | (0.069) | 0.084*** | (0.024) |
| Adj. $R^2$ | 0.658 | | 0.406 | | 0.390 | | 0.823 | |
| **Model (2):** R&D Expenditure (Observations: 2,335; Firms: 895) | | | | | | | | |
| $\ln(Markup_{i,t-1})$ | – 0.845*** | (0.143) | – 2.030*** | (0.183) | – 3.562*** | (0.630) | 0.029 | (0.172) |
| $\ln(R\&DExp_{i,t-1})$ | 0.052*** | (0.012) | 0.052*** | (0.011) | – 0.011 | (0.100) | 0.053 | (0.038) |
| Adj. $R^2$ | 0.650 | | 0.394 | | 0.417 | | 0.805 | |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| 2-digit Industry FE | Yes | | Yes | | Yes | | Yes | |

The table reports results from pooled OLS panel regressions for the matched sample of ZEW's MIP and Bureau van Dijk's Orbis database. Dependent variable is the natural logarithm of total factor productivity in year t (obtained from the production-function estimation in log scale). Independent variables of interests are the natural logarithm of firm-level price markups and innovation in year t–1. Reported are results for four alternative definitions of innovation. Model (1) and (2) use the natural logarithm of innovation and R&D expenditure, respectively. Coefficients can be interpreted as elasticities. Model (1) and (2) additionally include a dummy variable that is 1 if firm does not invest in innovation and R&D, respectively (not reported). In model (3) and (4), product and process innovation are dummy variables related to the 3-year period t–1 to t–3. Coefficients indicate the percentage change in productivity when the innovation dummy changes from 0 to 1. The number of observations / firms refers to the sample for the total economy (manufacturing, trade, and services). Standard errors are clustered at firm level. * p < 0.1, ** p < 0.05, *** p < 0.01.
Souce: Authors' own calculations.

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determinant of productivity. Notice that, once we control for innovation in the productivity estimation to capture the indirect effect, our estimates for the direct effect of price markups on productivity do not change much. The estimated elasticities for price markups in Table 14 are analogous to the coefficients reported in column (2) of Table 11. Comparing the combined effect of markups on productivity as estimated following equation (11) (not controlling for innovation) with the effects estimated following equation (13) (controlling for innovation), we find quantitatively similar results. For these estimates, we have estimated the direct productivity effect of markups assuming innovation to be exogenously given. In the next section, we allow for innovation to be endogenously determined.

## 6.4 Joint Estimation of Innovation and Productivity

In order to estimate direct and indirect effects of competition on productivity, we jointly estimate a system of equations of innovation and productivity. The first equation describes the impact of competition on innovation, more specifically, we explain the innovation (or R&D) expenditure in period $t-1$ by competition (markups) in year $t-2$ and a set of control variables:

$$(14)\quad \ln(Inno/R\&DExp_{i,t-1}) = f(\ln(Markup_{i,t-2}), \cdot)$$

The second equation then explains productivity in period $t$ by competition (markups) and innovation (or R&D) expenditure, both measured in period $t-1$.

$$(15)\quad \ln(Productivity_{it}) = f(\ln(Markup_{i,t-1}), \ln(Inno/R\&DExp_{i,t-1}), \cdot)$$

While for the results in Table 14, we have assumed innovation to be exogenously given, this system of equations (14) and (15) implies that innovation (or R&D) expenditure is endogenously determined by lagged markups. Furthermore, we allow the error terms of both equations to be correlated.

Overall, this allows to disentangle the direct effect of markups on productivity and the indirect effect via innovation.

We report the results for the system of equations in Table 15, using innovation expenditure (System 1) and R&D expenditure (System 2) as dependent variables in equation (14) [Equation 1] and total factor productivity as dependent variable in equation (15) [Equation 2]. We also report results for the system with labor productivity in Table 18 in the appendix.

Comparing the results in Table 15 (System 1) and Table 13, we find that the estimated effect of (lagged) markups on innovation expenditure obtained from the two-equation system (in equation (14)) is weaker than the effect from a separate innovation equation (in equation (12)). We observe the starkest difference in manufacturing where the estimated elasticity is -2.7, as compared to -3.7 in Table 13. This difference means that the reduction of innovation expenditure in response to a 1 percent increase in price markups drops by 1 percentage point, from 3.7 percent to 2.7 percent. When considering R&D expenditure (System 2 in Tables 15), the results obtained from the two-equation system and those from a separate innovation equation are virtually the same.

Table 15 provides the information needed for an assessment of the direct and indirect effects of price markups on productivity. For ease of exposition in this decomposition exercise, we report the respective elasticities in Table 16. The combined effect is the estimated coefficient reported

TABLE 15: **Direct and Indirect Effect of Competition on TFP (System Estimation)**

| | Total (a) | | Manufacturing (b) | | Trade (c) | | Services (d) | |
|---|---|---|---|---|---|---|---|---|
| **System 1 – Equation 1:** Dep. Var.: $\ln(\text{InnoExp}_{i,t-1})$ (Observations: 2,016) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-2})$ | – 1.512*** | (0.497) | – 2.699*** | (0.788) | – 1.812 | (2.244) | – 1.594** | (0.698) |
| $R^2$ | 0.346 | | 0.341 | | 0.104 | | 0.373 | |
| **System 1 – Equation 2:** Dep. Var.: $\ln(\text{TFP}_{it})$ (Observations: 2,016) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-1})$ | – 0.789*** | (0.072) | – 2.088*** | (0.104) | – 3.080*** | (0.486) | 0.271** | (0.121) |
| $\ln(\text{InnoExp}_{i,t-1})$ | 0.052*** | (0.007) | 0.052*** | (0.006) | 0.120 | (0.098) | 0.109*** | (0.019) |
| $R^2$ | 0.634 | | 0.305 | | 0.429 | | 0.778 | |
| **System 2 – Equation 1:** Dep. Var.: $\ln(\text{R\&DExp}_{i,t-1})$ (Observations: 1,922) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-2})$ | – 1.565*** | (0.481) | – 4.018*** | (0.789) | 0.598 | (1.959) | – 1.714*** | (0.568) |
| $R^2$ | 0.403 | | 0.381 | | 0.068 | | 0.477 | |
| **System 2 – Equation 2:** Dep. Var.: $\ln(\text{TFP}_{it})$ (Observations: 1,922) | | | | | | | | |
| $\ln(\text{Markup}_{i,t-1})$ | – 0.821*** | (0.077) | – 1.940*** | (0.106) | – 3.595*** | (0.418) | 0.411** | (0.194) |
| $\ln(\text{R\&DExp}_{i,t-1})$ | 0.061*** | (0.008) | 0.051*** | (0.006) | 0.099 | (0.200) | 0.219*** | (0.056) |
| $R^2$ | 0.610 | | 0.303 | | 0.115 | | 0.597 | |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| 2-digit Industry FE | Yes | | Yes | | Yes | | Yes | |

The number of observations refers to the sample for the total economy. The table reports results from a two-equation system estimation for the matched sample of ZEW's MIP and Bureau van Dijk's Orbis database. In System 1, the dependent variable in Equation 1 is the natural logarithm of innovation expenditure in year t – 1; in System 2, the dependent variable in Equation 1 is the natural logarithm of R&D expenditure in year t – 1. In both systems, the dependent variable in Equation 2 is the natural logarithm of total factor productivity in year t. The indirect effect of competition is captured by the natural logarithm of firm-level price markups in year t – 2 in Equation 1. The direct effect of competition is measured via the natural logarithm of firm-level price markups in year t – 1 in Equation 2. Both equations control for year FE and 2-digit industry effects, and Equation 1 additionally includes firm size (as ln(Assets)) as control. Standard errors are clustered at firm level. * p < 0.1, ** p < 0.05, *** p < 0.01.
Souce: Authors' own calculations.

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TABLE 16: **Combined, Direct, and Indirect Effect on Competition in TFP**

| | Total (a) | | Manufacturing (b) | | Trade (c) | | Services (d) | |
|---|---|---|---|---|---|---|---|---|
| **System 1:** Innovation variable is ln ($InnoExp_{it}$) | | | | | | | | |
| Combined effect | – 0.680*** | (0.093) | – 1.940*** | (0.175) | – 3.552*** | (0.440) | 0.057 | (0.103) |
| Direct effect | – 0.789*** | (0.072) | – 2.088*** | (0.104) | – 3.080*** | (0.486) | 0.271** | (0.121) |
| Indirect effect (Approximation) | – 0.079 | | – 0.140 | | – 0.217 | | – 0.174 | |
| **System 2:** Innovation variable is ln ($R\&DExp_{it}$) | | | | | | | | |
| Combined effect | – 0.680*** | (0.093) | – 1.940*** | (0.104) | – 3.552*** | (0.440) | 0.057 | (0.103) |
| Direct effect | – 0.821*** | (0.077) | – 1.940*** | (0.106) | – 3.595*** | (0.418) | 0.411** | (0.194) |
| Indirect effect (Approximation) | – 0.095 | | – 0.205 | | 0.059 | | – 0.375 | |

The table reports the combined effect of lagged markups on total factor productivity (from Table 11), the direct effect (from Table 15, Equation 2), and the approximated indirect effect. The latter is calculated as the effect of price markups on innovation (from Table 15, Equation 1) times the effect of innovation on productivity (from Table 15, Equation 2). Direct and indirect effects do not need to sum up to the combined effect. The reported indirect effects in columns (a), (b), and (d) are based on statistically significant estimated elasticities (the underlying estimated elasticities in column (c) are not statistically significant). They do not otherwise carry any claims of inference.
Souce: Authors' own calculations.

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in column (2) of Table 11. The direct effect of competition is the estimated coefficient for lagged price markups in Equation 2 of Table 15. For both innovation variables (Systems 1 and 2) and across various sub-samples the two productivity-markup elasticities are of the same sign and of a similar order of magnitude. For the manufacturing and trade sector, our results support the conventional view that increased competition raises firm-level productivity, in line with work by Schmitz (2005), Matsa (2011), or Bloom et al. (2019).

For the services sector, the combined effect of price markups in Table 11 (as well as the effect of price markups in Table 14 when innovation is assumed to be exogenous) is positive but insignificant. With our system estimation approach, the (direct) effect is now positive and statistically significant. This puts the results for total factor productivity in line with the earlier results for labor productivity.[41] We find robust evidence for a positive effect of price markups on productivity. Put differently, in the services sector, increased competition lowers firm-level productivity. These results are at odds with the conventional view but in line with the work by Autor et al. (2020) or Hsieh and Rossi-Hansberg (2019).

41 See also Table 20 in the appendix in which we report system-estimation results for labor productivity.

The indirect effect in Table 16 is an approximation, equal to the product of the coefficient on price markups in Equation 1 (Table 15) and the coefficient on innovation in Equation 2 (Table 15).[42] We report in boldface those indirect effects that are based on statistically significant estimation coefficients. The figures in Table 16 yield a number of interesting observations from our effect-decomposition exercise.

First, we separately estimate the indirect effect and find significant results for manufacturing and the services sector (as well as for the aggregated total economy). Furthermore, the results are as expected and in line with existing literature. The indirect effect of price markups on productivity is negative – more competition lowers productivity because it lowers innovation expenditure which in return lowers productivity.

Second, in manufacturing, the indirect effect is small relative to the direct effect. The difference of the two effects is of an order of magnitude of 10 (for R&D expenditure, System 2) to 15 (for innovation expenditure, System 1). This means, while the indirect effect reinforces the direct effect

42 Consider the following example: the coefficient of price markups (in $t$-2) on innovation expenditure (in $t$-2) is -2, and the coefficient of innovation (in $t$-1)on productivity (in $t$) is 0.25. Both coefficients can be interpreted as elasticities. The indirect effect of price markups on productivity is $-2 \times 0.25 = -0.5$. The reported elasticities for the effect of price markups in $t$-1 are approximations as they capture the indirect effect of price markups in $t$-2(!) on productivity in $t$.

(to obtain the combined effect), this contribution is relatively small.

Third, in the services sector, we see countervailing effects, with a relatively large negative indirect effect offsetting the positive direct effect. The direct effect (e. g., via managerial practices) implies a 0.27 percent increase of productivity in System 1 and a 0.41 percent increase in System 2 in response to a 1 percent increase in price markups. At the same time, our approximations of the indirect effect (by way of a firm’s innovation activities that are a function of price markups) suggest a -0.17 percent (System 1) and -0.38 percent (System 2) decrease in response to a 1 percent increase in price markups.

Last, we do not find evidence for an indirect effect in the trade sector. R&D and innovation play a subordinated role in trade, and changes in the competitive environment have little impact on how much firms innovate.

# 7 Conclusion

In this report, we have presented results from our firm-level estimation of price-cost margins in the form of price markups (i. e., price above marginal cost) on a sample of more than 12,000 German firms over the period of 2007 through 2016. We find that price markups across industries are at 30-45 percent, with the highest markups in the services sector and the lowest in trade. The estimates are significantly lower than those reported for the U.S. (De Loecker et al., 2020), but in line with estimates for Europe (De Loecker and Eeckhout, 2018; Cavalleri et al., 2019).

Price markups are an important determinant of productivity, explaining as much as 40 percent of the variation of firm-level total factor productivity. We further show that markups have a negative effect on productivity in manufacturing and trade. A 1 percent increase in price markups results in a 2 percent and 3.5 percent decrease in productivity for firms in the manufacturing and trade sector, respectively. When interpreting higher levels of price markups as lower levels competition, these results are in line with the “quiet-life hypothesis” (Hicks, 1935) or the notion of “X-inefficiency” (Leibenstein, 1966) and comport with recent empirical findings (Schmitz, 2005; Matsa, 2011; Bloom et al., 2019; Backus, 2019). Our findings further suggest that pro-competitive policies (with the effect of curbing firm’s market power and lowering firm-level price markups) have the potential to increase firm-level productivity – in manufacturing and trade. In the services sector, however, our results are reversed, calling for a differentiated policy approach.

When separately estimating the *direct* effect of price markups on productivity (keeping innovation constant) and the *indirect* effect (where price markups affect innovation and innovation in turn is a determinant of productivity), we find that, in manufacturing, the negative indirect effect is relatively small but reinforces the negative direct effect. In services, on the other hand, the negative indirect effect is sizable and partially offsets the positive direct effect. Last, for the trade sector, we do not find a significant indirect effect and conclude that a firm’s innovation activity does not contribute to the effect of competition (or the lack thereof) on productivity in that sector.

Our findings of relatively strong direct effects of price markups (in comparison to the innovation-centered indirect effects) in all sectors but services highlight the potential for a well-tailored competition policy approach in society’s effort to tackle the productivity slowdown. This is particularly true for the trade sector, where the effect of competition on R&D and innovation is of limited significance for the determination of firm-level productivity. For services, on the other hand, the interdependence of competition and innovation in their effect on productivity must be taken into account as the indirect effect partially offsets the direct effect of competition on productivity. Considering one without the other will be misguiding.

This study zooms in on the effect of price markups on productivity and must put aside other areas – no less important – in which markups affect economic outcomes. Markups have implications for labor markets, as they are often linked to the decrease of labor shares, stagnating real wages, and wage inequality. Markups are also said to have implications for financial markets, since increased market power is associated with a decrease in the capital share. These and other implications directly affect firms’ output and, as a consequence, domestic product (De Loecker et al., 2020). For these reasons, the evaluation of market power is highly relevant from a political perspective; not only with regard to competition policy, but also with regard to labor and capital market regulation or innovation policy.

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# 9 Appendix

## 9.1 Further Details on Sample Construction

Our sample does not contain data on physical inputs (except for the number of employees) nor on physical output. Instead, we observe the necessary variables in terms of their value in euros (as of a given year). To make observations comparable across time, we apply a deflator.[43] For *revenue, material costs,* and *capital stock* we use the producer price indices (PPI) provided by Eurostat.[44] For labor costs, we use a labor costs deflator provided by Eurostat.

- For Nace section Manufacturing (C), we use the two-digit Nace divisions PPIs when available for all years; otherwise, we use the PPI associated with the main Nace section.[45]
- For Nace section Wholesale and retail trade (G), we construct a PPI using data on revenue and deflated revenue on a two-digit Nace code level from Eurostat. We construct the PPI using the formula

$$\frac{revenue_t}{deflated\ revenue_t} * 100. \tag{15}$$

- For the remaining Nace sections Transportation and storage (H), Accommodation and food service activities (I), Information and communication (J), Real estate activities (L), Professional, scientific and technical activities (M), and Administrative and support service activities (N) a common ("services") PPI is used (available only for 2006 onwards).
- Last, *labor costs* are deflated by using a Eurostat labor costs deflator that is based on the respective Nace section level.

43 From Orbis, we obtain data on the closing date (i.e., the date the account was closed and the variables were collected). The relevant period for a firm is therefore from closing date in $t$ to the one in $t+1$. While the closing date of many firms is December 31st, some close at January 1st or other dates throughout the year. This misalignment of calendar year and fiscal year poses an issue. Because we only have annual deflators, we have to arbitrarily choose how we deflate our data. This means, for a misaligned fiscal year, we have to assign it to a calendar year to be able to use our deflators. We choose to use July 1st as a cutoff date. For example, all variables collected from July 1st, 2005 to June 30th, 2006 are deflated with the 2005 PPI.

44 The relevant time series can be found at https://ec.europa.eu/eurostat/en/data/database.

45 This is the case for Nace division C33.

## 9.2 Industry Breakdown

In Table 17, we provide the number of firms and number of observations for each of the individual 12 Nace sections. Table 2 in the main text provides information for sections manufacturing (C), trade (G), and services (H, I, J, L, M, and N).

## 9.3 Productivity Impact of Markups: Heterogeneity over Time

We further ask if the productivity-markup relationship changes over time and, if so, do the estimated elasticities follow a particular time trend? In Table 18, we present results from regressions where we interact the explanatory variable of interest (firm-level price markups) with year dummies (using 2007 as our base year). We report the baseline elasticity (for 2007) and the year-interaction terms for the total economy and separately for each sector.

The estimated productivity-markup elasticities are fairly constant over time. For trade and services, we do not see any significant changes over time in how markups affect productivity. An exceptions is manufacturing where we observe a weaker (yet still negative) relationship between markup and productivity around the beginnings of the European sovereign debt crisis (2008) and in the more recent years in our estimation sample (2015-2016). However, these effects also vanish in the intertemporal estimation when we study the link between lagged markup and productivity in Table 19.

TABLE 17: **Number of Firms and Observations by Industry (Nace Section)**

| Nace Section | | Firms | Obs. |
|---|---|---|---|
| C | Manufacturing | 5,435 | 33,942 |
| G | Trade (Wholesale and retail trade) | 3,671 | 22,521 |
| H | Logistics (Transportation and storage) | 659 | 4,126 |
| I | Accomondation & food (Accommodation and food service activities) | 187 | 1,013 |
| J | IT (Information and communication) | 624 | 3,592 |
| L | Real estate (Real estate activities) | 120 | 563 |
| M | Professional (Professional, scientific, and technical activities) | 814 | 4,681 |
| N | Administrative (Administrative and support service activities) | 453 | 2,478 |
| | Total | 11,963 | 72.916 |

The table contains, for each of the 8 selected Nace sections in our estimation sample, the total number of firms and the total number of observations. Throughout this report, we use the abbreviated section names as introduced in this table.
Source: Numbers based on data obtained from Bureau van Dijk's Orbis database and authors' own calculations.

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TABLE 18: **Productivity-Markup Elasticities Over Time**

| Dependent variable: ln (Productivity$_{it}$) | Total (1) | | Manufacturing (2) | | Trade (3) | | Services (4) | |
|---|---|---|---|---|---|---|---|---|
| ln (Markup$_{it}$) | – 1.3840*** | (0.0847) | – 2.3630*** | (0.142) | – 4.1690*** | (0.235) | – 0.0338 | (0.0627) |
| x 2008 | – 0.0867 | (0.0769) | – 0.0446 | (0.135) | 0.0776 | (0.234) | – 0.0168 | (0.0533) |
| x 2009 | – 0.0146 | (0.0827) | 0.2580* | (0.139) | 0.2190 | (0.238) | – 0.0201 | (0.0580) |
| x 2010 | – 0.0189 | (0.0871) | 0.0743 | (0.148) | – 0.0207 | (0.255) | – 0.0172 | (0.0594) |
| x 2011 | – 0.0621 | (0.0872) | 0.0328 | (0.148) | – 0.1970 | (0.269) | 0.0059 | (0.0598) |
| x 2012 | – 0.1350 | (0.0871) | 0.0652 | (0.148) | – 0.0087 | (0.261) | – 0.0539 | (0.0612) |
| x 2013 | – 0.0893 | (0.0875) | 0.0923 | (0.147) | – 0.0386 | (0.265) | – 0.0439 | (0.0619) |
| x 2014 | – 0.0345 | (0.0896) | 0.1650 | (0.150) | – 0.0294 | (0.268) | – 0.0065 | (0.0634) |
| x 2015 | 0.0215 | (0.0894) | 0.2650* | (0.153) | – 0.1760 | (0.270) | 0.0141 | (0.0638) |
| x 2016 | 0.0488 | (0.0948) | 0.3670** | (0.168) | – 0.1170 | (0.296) | 0.0264 | (0.0679) |

The table reports results from pooled OLS regressions. Dependent variable is the natural logarithm of total factor productivity (obtained from the production-function estimation in log scale). Independent variable of interest is the natural logarithm of firm-level price markups and year-interaction terms (base year: 2007). Reported coefficients are interpreted as elasticities. For more estimation details, see the notes for Table 8. Robust standard errors in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.
Souce: Authors' own calculations.

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TABLE 19: **Productivity-Markup Elasticities (Lagged) Over Time**

| Dependent variable: ln(Productivity$_{it}$) | Total (1) | | Manufacturing (2) | | Trade (3) | | Services (4) | |
|---|---|---|---|---|---|---|---|---|
| ln(Markup$_{i,t-1}$) | – 1.4660*** | (0.0961) | – 2.2540*** | (0.169) | – 4.4270*** | (0.286) | – 0.1340* | (0.0725) |
| x 2009 | – 0.0337 | (0.0852) | 0.0246 | (0.159) | 0.4380* | (0.262) | 0.0670 | (0.0602) |
| x 2010 | 0.0269 | (0.0937) | 0.2280 | (0.163) | 0.4880* | (0.292) | 0.0563 | (0.0654) |
| x 2011 | – 0.0076 | (0.0949) | – 0.0647 | (0.170) | 0.1700 | (0.303) | 0.0885 | (0.0654) |
| x 2012 | – 0.0450 | (0.0953) | – 0.0363 | (0.172) | 0.0811 | (0.307) | 0.0551 | (0.0664) |
| x 2013 | – 0.0503 | (0.0966) | 0.0087 | (0.170) | 0.2120 | (0.307) | 0.0064 | (0.0686) |
| x 2014 | – 0.0492 | (0.0975) | 0.0453 | (0.173) | 0.1510 | (0.312) | 0.0399 | (0.0702) |
| x 2015 | 0.0353 | (0.0995) | 0.1460 | (0.176) | 0.1400 | (0.315) | 0.0786 | (0.0711) |
| x 2016 | 0.1220 | (0.105) | 0.2080 | (0.189) | 0.0995 | (0.346) | 0.1070 | (0.0752) |

The table reports results from pooled OLS regressions. Dependent variable is the natural logarithm of total factor productivity (obtained from the production-function estimation in log scale). Independent variable of interest is the lagged natural logarithm of firm-level price markups and year interaction terms (base year: 2008). Reported coefficients are interpreted as elasticities. For more estimation details, see the notes for Table 8. Robust standard errors in parentheses. * p < 0.1, ** p < 0.05, *** p < 0.01.
Source: Authors' own calculations.

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TABLE 20.: **Direct and Indirect Effect of Competition on Labor Productivity (System)**

| | Total (a) | | Manufacturing (b) | | Trade (c) | | Services (d) | |
|---|---|---|---|---|---|---|---|---|
| **System 1 – Equation 1:** Dep. Var.: ln(InnoExp$_{i,t-1}$) (Observations: 2,026) | | | | | | | | |
| ln(Markup$_{i,t-2}$) | – 1.480*** | (0.496) | – 2.771*** | (0.787) | – 1.305 | (2.271) | – 1.500** | (0.693) |
| $R^2$ | 0.344 | | 0.341 | | 0.103 | | 0.377 | |
| **System 1 – Equation 2:** Dep. Var.: ln (Labor Productivity$_{it}$) (Observations: 2,026) | | | | | | | | |
| ln(Markup$_{i,t-1}$) | – 0.544*** | (0.071) | – 2.038*** | (0.110) | – 3.401 | (0.397) | 0.533*** | (0.097) |
| ln(InnoExp$_{i,t-1}$) | 0.047*** | (0.007) | 0.064*** | (0.006) | 0.082 | (0.084) | 0.065*** | (0.015) |
| $R^2$ | 0.316 | | 0.250 | | 0.168 | | 0.349 | |
| **System 2 – Equation 1:** Dep. Var.: ln(R&DExp$_{i,t-1}$) (Observations: 1,932) | | | | | | | | |
| ln(Markup$_{i,t-2}$) | – 1.551*** | (0.481) | – 4.074*** | (0.787) | 0.957 | (1.999) | – 1.617*** | (0.565) |
| $R^2$ | 0.402 | | 0.381 | | 0.070 | | 0.483 | |
| **System 2 – Equation 2:** Dep. Var.: ln (Labor Productivity$_{it}$) (Observations: 1,932) | | | | | | | | |
| ln(Markup$_{i,t-1}$) | – 0.568*** | (0.075) | – 1.871*** | (0.112) | – 3.740 | (0.316) | 0.614*** | (0.131) |
| ln(R&DExp$_{i,t-1}$) | 0.054*** | (0.008) | 0.063*** | (0.006) | – 0.040 | (0.151) | 0.123*** | (0.036) |
| $R^2$ | 0.302 | | 0.252 | | 0.514 | | 0.151 | |
| Year FE | Yes | | Yes | | Yes | | Yes | |
| 2-digit Industry FE | Yes | | Yes | | Yes | | Yes | |

The number of observations refers to the sample for the total economy. The table reports results from a two-equation system estimation for the matched sample of ZEW's MIP and Bureau van Dijk's Orbis database. In System 1, the dependent variable in Equation 1 is the natural logarithm of innovation expenditure in year t – 1; in System 2, the dependent variable in Equation 1 is the natural logarithm of R&D expenditure in year t – 1. In both systems, the dependent variable in Equation 2 is the natural logarithm of labor productivity in year t. The indirect effect of competition is captured by the natural logarithm of firm-level price markups in year t – 2 in Equation 1. The direct effect of competition is measured via the natural logarithm of firm-level price markups in year t – 1 in Equation 2. Both equations control for year FE and 2-digit industry effects, and Equation 1 additionally includes firm size (as ln(Assets)) as control. Standard errors are clustered at firm level. * p < 0.1, ** p < 0.05, *** p < 0.01.
Source: Authors' own calculations.

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## 9.4 Direct and Indirect Effect of Competition on Labor Productivity

We report in Table 20 the results for the system of equations (equations (14) and (15)), using innovation expenditure (System 1) and R&D expenditure (System 2) as dependent variables in equation (14) [Equation 1] and labor productivity as dependent variable in equation (15) [Equation 2]. The results reported in the main text (with total factor productivity as the dependent variable in equation (15) and summarized in Table 15 follow through.

## 9.5 Estimating Price Markups

### 9.5.1 Obtaining the Output Elasticity

#### General Setup

To obtain an estimate of the output elasticity, we need to estimate the firm's production function. We follow the control-function approach in Ackerberg et al. (2015). We restrict our attention to production functions with a scalar Hicks-neutral productivity term and common technology parameters across the set of producers in the same industry. These restrictions imply the following production function:

(16) $Q_{it} = F\,(X^1_{it}, \ldots, X^V_{it}, K_{it})\ exp\,\omega_{it}$

Let $Y_{it}$ denote the level of observable output of firm $i$ in $t$. Further, assume that observable output is stochastic with $Y_{it} = Q_{it}\, exp\, \epsilon_{it}$ where $\epsilon_{it}$ are i.i.d. shocks which include measurement errors and unanticipated shocks to production. Given $Y_{it}$ we obtain

(17) $Y_{it} = F\,(X^1_{it}, \ldots, X^V_{it}, K_{it})\ exp\,(\omega_{it} + \epsilon_{it})$

Taking logs of this general form production function, we obtain:

(18) $y_{it} = f(x^1_{it}, \ldots, x^V_{it}, k_{it}) + \omega_{it} + \epsilon_{it}$

This log-production function will form the basis of our estimation.

#### Assumptions

In order to identify the parameters in a production function (18), we make a number of assumptions (Ackerberg et al., 2015). Given Assumptions 1 and 2, firms do not know future productivity shocks but only their distribution.

**Assumption 1.** A firm's information set at period t, that is $l_{it}$, includes current and past productivity shocks $\{\omega_{i\tau}\}^t_{\tau=0}$ but does not include future productivity shocks $\{\omega_{i\tau}\}^\infty_{\tau=t+1}$. The transitory shocks satisfy $E[\epsilon_{it} | l_{it}] = 0$.

**Assumption 2.** Productivity shocks evolve according to the distribution

$p(\omega_{it+1} | I_{it}) = p(\omega_{it+1} | \omega_{it})$

Assumption 3 states that the level of capital available for the production process in period $t$ is decided in period $t-1$. Labor input available for production in $t$ is chosen after capital but before $t$. This latter part of the assumption can be motivated by costs of labor turnover (e.g., menu costs such as hiring and firing of employees).

**Assumption 3.** Firms accumulate capital according to

$k_{it} = \kappa(k_{i,t-1}, i_{i,t-1})$

where investment $i_{it-1}$ is chosen in period $t-1$. Labor input $l_{it}$ is chosen at period $t-b$ (with $0 < b < 1$).

Per Assumption 4, materials are an input variable that can be freely adjusted after the realization of the productivity shock in $t$.

**Assumption 4.** Firms' variable input demand is given by

$m_{it} = \tilde{f}_t\,(k_{it}, l_{it}, \omega_{it}, z_{it})$

To summarize the timing of decisions and shocks relevant for production in $t$: the firm chooses the capital level in $t-1$ upon which the firm decides how much labor to employ (in $t-b$).

We will further assume strict monotonicity of the materials input function $\tilde{f}(\cdot)$. We make this assumption to guarantee the existence of the inverse of $\tilde{f}(\cdot)$ as our input demand $\omega_{it} = \tilde{f}_t^{-1}(k_{it}, l_{it}, m_{it})$. This allows us to use materials $m_{it}$ as a proxy for $\omega_{it}$. This assumption holds as long as more productive firms do not set disproportionately higher markups than less productive firms (Levinsohn and Melitz, 2006).

**Assumption 5.**

$m_{it} = \tilde{f}_t\,(k_{it}, l_{it}, \omega_{it}, z_{it})$ *is strictly increasing in* $\omega_{it}$.

Last, Assumption 6 guarantees the comparability of the estimated values across firms, given our data are in monetary values rather than physical units.

**Assumption 6.** Firms are price takers in both input and output markets and they face the same prices for equivalent inputs or outputs.

### Production Function Estimation

We use the two-step control function estimation by Ackerberg et al. (2015). Following De Loecker and Scott (2016), we rely our estimation on a structural value added production function:

$$(19)\quad Y_{it} = min[\gamma_m M_{it}, F(L_{it}, K_{it}) exp(\omega_{it})] exp(\epsilon_{it})$$

Hence, in the optimum the cost minimizing firm sets the marginal product of material inputs equal to the marginal product of labor and capital. For this reason, both of the following equations hold:

$$(20)\quad Y_{it} = \gamma_m M_{it} exp(\epsilon_{it})$$

$$(21)\quad Y_{it} = F(L_{it}, K_{it}) exp(\omega_{it}+\epsilon_{it})$$

The complementarity between material inputs with labor and capital allows for different estimation procedures of the first stage, which either relies on equation 20 or equation 21. Both specifications theoretically yield the same production function estimates. In the following, we use equation 6 for the first stage of the procedure.

**Stage 1:** In the first stage, we separate unobserved productivity $\omega_{it}$ from the error term $\epsilon_{it}$. Therefore, we use the inverse of the variable input demand function $\omega_{it}=\widetilde{f_t^{-1}}(k_{it}, l_{it}, z_{it})$ and estimate non-parametrically:

$$(22)\quad \begin{aligned} Y_{it} &= \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \widetilde{f_t^{-1}}(k_{it}, l_{it}, z_{it}) + \epsilon_{it} \\ &= \phi(k_{it}, l_{it}, z_{it}) + \epsilon_{it} \end{aligned}$$

Note that the parameter $z_{it}$ captures fixed effects and non-linear transformations of the production inputs labor and capital. The moment condition in the first stage – following Ackerberg et al. (2015) – is

$$(23)\quad E[\epsilon_{it}|I_{it}]=E[y_{it} - \phi_{it}(k_{it}, l_{it}, z_{it})|I_{it}]=0$$

From this first stage, we obtain the expected output $\widehat{\phi}_{it}$ and an estimate for $\epsilon_{it}$.

**Stage 2:** In the second stage, we estimate the production function coefficients. Assumptions 1 and 2 imply that we can express $\omega_{it}$ as a function of its realization in the previous period and an innovation term $\xi_{it}$:

$$(24)\quad \omega_{it}=g(\omega_{it-1})+\xi_{it}$$

By construction, $E[\xi_{it}|I_{it-1}]=0$. The term $\xi_{it}$ can be thought of as capturing innovation to productivity. Moreover, given our first-stage estimation, we can express $\omega_{it}$ as

$$(25)\quad \omega_{it}=\widehat{\phi}_{it}(k_{it}, l_{it}, z_{it}) - \beta_0 + \beta_k k_{it} + \beta_l l_{it}$$

Combining equations (24) and (25) we get the following equation:

$$(26)\quad \omega_{it}=g(\widehat{\phi}_{it-1}(k_{it-1}, l_{it-1}, z_{it-1}) - \beta_0 + \beta_k k_{it-1} + \beta_l l_{it-1}) + \xi_{it}$$

We estimate equation (26) using standard GMM techniques to obtain the estimates of the production function parameters. Given our assumptions the moment conditions are:

$$(27)\quad E\left(\xi_{it}(\beta)\begin{pmatrix} 1 \\ k_{it} \\ l_{it-1} \end{pmatrix}\right) = 0.$$

### Implementation

To estimate price markups, the cost share of a variable input (over revenue) and an estimate of the output elasticity are required. We choose labor (the number of employees) to be the variable input which will be the basis for the markup estimation. To obtain output elasticities, we estimate a sector-specific production function for each of the 12 Nace Rev. 2 industry codes. In order to estimate production functions, we need to make an assumptions about the functional forms of the production functions.

When using the structural value added production technology the markup equation needs to be adjusted since materials are not in the estimated production function but still influence marginal costs. Given the particular form of the production function, marginal costs are given by

$$(28)\quad \lambda_{Qit} = \lambda_{Fit} + \frac{P_{Mit}}{\beta_m},$$

where $\lambda_{Fit}$ are the marginal costs of the first part in operator and last term are the marginal costs of materials. In the markup estimation, this translate to

$$(29)\quad \mu_{it}=\frac{1}{\mu_{Fit}^{-1} + \alpha_{Mit}},$$

where $\mu_{Fit}$ is the markup estimator obtained with labor and $\alpha_{Mit}$ the cost share of materials (over revenue).

We use a Cobb-Douglas functional form for our structural value added production function. This assumption implies a constant elasticity of substitution. The output elasticity of the variable input labor is then:

(30) $\theta_{L,it} = ß_l$

For the first stage estimation of the production function, we apply a polynomial of 4th degree for $\Phi_{it}(k_{it}, l_{it}, m_{it})$. We further include industry (2-digit Nace industry codes) fixed effects and federal-state fixed effects. For the second stage of the estimation of the production function, we apply a 3rd degree polynomial for $g(\omega_{it-1})$.

### 9.5.2 Obtaining Expenditure Shares for Labor

Recall that observed output is:

(31) $Y_{it} = Q_{it} \, exp \epsilon_{it}$

With $\epsilon_{it}$ representing i.i.d shocks. We therefore do not directly observe the correct cost share of a variable input from the data. To remedy this problem, we utilize the estimate for $\epsilon_{it}$ obtained in stage 1 of our estimation procedure. We can compute the corrected expenditure share as follows:

(32) $$\widehat{\alpha_{it}^X} = \frac{P_{it}^X X_{it}}{P_{it} \frac{Y_{it}}{exp\,\widehat{\epsilon_{it}}}}$$

This correction eliminates any variation in cost shares that is not correlated with labor, capital, materials, and other firm characteristics that are included in the estimation of the production function.

### 9.5.3 Some Limitations

The approach by De Loecker and Warzynski (2012) to recover firm-level price markups from financial statement data has been widely used in the literature in recent years. The approach does – nevertheless – comes with a number of limitations. In the sequel, we briefly summarize the respective discussion in the literature (where it applies).

**Adjustment Costs of Input Variables** The estimation routine is executed under the assumption that labor is a static production input, which is in line with the notion that we can learn about markups from the optimal hiring decisions. However, if labor is a dynamic input due to adjustment costs such as hiring and firing, then in order to obtain consistent estimates of the production function one needs to rely on current labor to identify the coefficients on labor. The implication of this is that the wedge between a firm's output elasticity of labor and the share of the labor costs in sales will capture an additional component reflecting these adjustment costs. In this case, given that material inputs are potentially less prone to adjustment costs, one can estimate a gross output production function and compute markups using the output elasticity of materials and its expenditure share (De Loecker and Warzynski, 2012).

**Unobserved Prices** Using financial statement data, we do not observe physical quantities sold but use deflated sales revenue as a measure of output $Y$. As a consequence, the approach is potentially subject to an omitted price variable bias. This implies that the estimated markups may be underestimated because the expected correlation between inputs and prices is negative. Notice, however, that unobserved prices will likely impact only the level of price markups but not their evolution across time.

**Perfectly Competitive Input Markets** This assumption implies that firms take the prices on the input markets as given and no bargaining occurs. This assumption is not an innocuous one, and might not be satisfied in reality.

**Price Setting Behavior** Prices are set period by period, meaning that there are no price dynamics within a given period. To our knowledge, this issue has yet to be solved in the literature.

# 10 Lists

## List of Figures



## List of Tables

## Die Serie „Produktivität für Inklusives Wachstum“


Band 1:
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