Market Power Increase and Sectoral Heterogeneity: the Role of e-Commerce Platforms*

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Abstract

This paper studies the impact of e-commerce platforms on firms' market power. I present a model with firm heterogeneity, oligopolistic competition, and Input-Output linkages, in which firms use the platforms to lower their variable costs. The cost reduction can occur either (i) as a result of efficiency gains or (ii) via direct discounts on input prices. The increasing use of platforms contributes to the rise of market power because it transforms the cost structure of the firms. Platform users show lower marginal costs but higher overhead costs: since the benefits of the marginal costs reduction outweigh the increase in overhead costs, this gives them a competitive advantage, explaining the increase in market power. Once calibrated to US data, the model attributes one third of the increase in markups to the introduction of e-commerce platforms. At the sectoral level, the heterogeneity in platforms use explains up to 40% of the differences in market power trends across sectors.

Keywords: Market Power, Platforms, Sectoral Heterogeneity, Input-Output
JEL Codes: L1, D4, E2, D2

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1 Introduction

The US economy experienced a sharp increase in firms' market power, with profit margins, market concentration and price markups on the rise since the turn of the century. However, not all sectors were exposed to the trends to the same extent: many have shown no change, or even a decline, in these quantities.[1] During the same period, e-commerce platforms gained popularity as intermediaries between firms. Currently, almost one fifth of the total Business-to-Business (*B2B*) operations in the US is carried out through these platforms, although their use varies across firms and sectors.[2] This paper investigates the impact of e-commerce platforms on sectoral and aggregate market power dynamics.

To address this question, I build a tractable framework that links the rise of e-commerce platforms to the increase in market power. The setting is characterized by a finite number of sectors connected by an Input-Output (I-O) structure from Grassi (2017), and inspired by Atkeson and Burstein (2008). In the model, firms compete in a sequential two-stage game. In the first stage, firms can subscribe to the platforms to lower their variable costs of production. In the second stage, firms compete under Cournot oligopolistic competition.

Platforms connect buyers and sellers across sectors and allow firms to decrease their variable costs in exchange for subscription fees. The cost reduction can happen (i) due to improvements in the efficiency of input procurement, or (ii) thanks to discounts on input prices from the platforms.[3] As the two sources imply different dynamics, I present two alternative versions of the model, which isolate either one of the two channels.

In the baseline experiment, the economy is composed of 15 NAICS-2 sectors, whose features are calibrated to the US, and the distribution of platforms use targets data from Amazon Web Services. To quantify the impact of platforms on market power, this environment is contrasted to a counterfactual scenario that shares the same calibration, but in which platforms are absent: more than 30% of the increase in markups observed in the US since the nineties can be attributed to the use of digital platforms, and this holds under both versions of the model. However, the dynamics of aggregate productivity differ. Only in the first version of the model, where the subscription to the platforms leads to efficiency gains, aggregate productivity grows in response to the increasing use of platforms.

The mechanism is as follows. By subscribing to the platforms, firms can re-optimize their cost structure, changing the balance between overhead costs, represented here by

[1] De Loecker, Eeckhout, and Unger (2020) and Autor, Dorn, Katz, Patterson, and Van Reenen (2020); see Markiewicz and Silvestrini (2022) for a review of the literature on sectoral heterogeneity.

[2] These statistics come from an economic report by Statista. Moreover, De Fiore, Gambacorta, and Manea (2023) quantify the share of *B2B* operations over the global e-commerce sales to more than 80%.

[3] For instance, efficiency gains and direct discounts are highlighted in Forrester (2020), when discussing the benefits of Amazon Business Prime for its subscribers.

subscription fees, and variable costs. On the one hand, this increases markups mechanically, given that firms need higher margins to break-even on their costs, consistently with the discussion in De Loecker et al. (2020). On the other hand, the resulting variable cost advantage allows firms to expand and increase their profits, altering the distribution of market power. Larger firms can afford more expensive subscription bundles: as the benefits of the marginal costs reduction outweigh the increase in overhead costs, this further increases their cost advantage, driving the increase in market power and productivity.

The baseline study is followed by two additional experiments. In the first, I show the extent of shocks propagation through the I-O structure, demonstrating that the amplification is qualitatively and quantitatively relevant. In the second, I allow shocks to the platform subscription fees to be sector-specific, calibrating them to the change in sectoral overhead cost shares from Compustat. These platform shocks can explain up to 40% of the observed sectoral heterogeneity in markup trends.

Literature Review

There is a recent strand of literature which studies market power outcomes in environments characterized by endogenous production networks and I-O linkages. In an oligopolistic competition setting, Grassi (2017) shows how shocks are transmitted from granular firms to the economy, and how this process is amplified by the I-O structure.[4] I augment his model by allowing firms to invest endogenously via the platforms, while focusing on long-run dynamics instead of short-run transmission. Bridgman and Herrendorf (2021) study the increase in sectoral markups and the amplification through the I-O structure, discussing the pattern of the labor share in services vs. manufacturing. However, they abstract from oligopolistic competition and firm heterogeneity, key drivers in my paper, as they are instrumental to match the heterogeneity in market power outcomes observed empirically across firms.

Huang, Manova, and Pisch (2021) find that upstream sellers' markups are affected by the set of sellers their downstream buyers have access to. Still, the network structure and the quality of the buyers do not affect the markups of the buyers themselves: this is the dimension I study. Pellegrino (2023) develops a model where firm-level markups come from quality-adjusted productivity and network centrality. In my framework, I also introduce both the productivity and the network components, through the investment in

[4]This result echoes Basu and Fernald (2002), who stress the importance of I-O linkages for the amplification of sectoral shocks. More in general, several papers study the propagation of shocks through networks, see Carvalho and Tahbaz-Salehi (2019) for a survey of the literature. A non-exhaustive list goes from the seminal work by Hulten (1978) to the recent contributions by Jones (2011a), Jones (2011b), Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), Carvalho (2014), Acemoglu, Akcigit, and Kerr (2016), Baqaee (2018), Acemoglu and Azar (2020), Baqaee and Farhi (2020) and Bigio and La'o (2020).

the platforms, and relate them to market power trends. However, I focus on the rise of platforms, while he emphasises product similarity as a driver for market power. I view these works as complementary, since they all contribute to a unified view on the interplay between networks and market power: while Huang et al. (2021) study the market power of sellers, I focus on buyers', while Pellegrino (2023) introduces demand driven sources of market power, I discuss supply and input acquisition processes.

Regarding the decision to subscribe to the platforms, several papers link firm investment that generates a trade-off between overhead and variable costs to the rise of market power.[5] The seminal work by Sutton (1991) argues that the introduction of new sunk-cost technologies increased market concentration. Hortaçsu and Syverson (2015) and Ganapati et al. (2018) study the retail and wholesale sectors, respectively, connecting the rise of technologies with high fixed costs and low marginal costs to market concentration. Hsieh and Rossi-Hansberg (2023) show that the increase in concentration is driven by services, retail and wholesale, and claim that this is the result of a similar technological change. The framework I present differs from these models in some relevant dimensions. First, this model is embedded with sectoral heterogeneity, as the incentives to invest in the platforms are sector-specific due to the I-O structure. Second, the benefits of the subscription can be orthogonal to the productivity process.[6]

Aghion, Bergeaud, Boppart, Klenow, and Li (2019), De Ridder (2019) and Olmstead-Rumsey (2019) discuss the increase in markups in environments characterized by a similar technological trade-off. Their results rely on the fall of the innovation efficiency of laggards firms and on the rise of intangible capital to endogenously generate the observed market power trends. Nonetheless, they abstract from oligopolistic competition, strategic interactions and sectoral dynamics, which are the core features of my paper. Indeed, given that market power patterns are strongly heterogeneous across sectors, proposing a mechanism that holds at different levels of aggregation is crucial.

More in general, the abatement of variable costs via the platforms echoes the empirical evidence on input acquisition processes, and how their improvements impact firms' performances through lower marginal costs and higher product quality: the mechanism is studied in Goldberg, Khandelwal, Pavcnik, and Topalova (2010), Manova, Wei, and Zhang (2015), Antras, Fort, and Tintelnot (2017), Fieler, Eslava, and Xu (2018), Bernard, Moxnes, and Saito (2019), and Boehm and Oberfield (2020). This implies that larger firms

[5]Alternatively, similar dynamics can arise in a problem of vertical integration, although the latter entails a joint profit maximization between buyers and sellers post-integration in the second stage, or with increasing return to scale (IRS) in production, see Chiavari (2021) and Shanks (2023).

[6]Moreover, in my model the investment in the platforms is nil if linkages between sectors are absent. This is not the case in models where the I-O structure acts as a shock propagator, see for instance Barrot and Sauvagnat (2016), Grassi and Sauvagnat (2019) or Bigio and La'o (2020).

tend to have lower input prices, see Bøler, Moxnes, and Ulltveit-Moe (2015). Moreover, Baqaee, Burstein, Duprez, and Fahri (2023) find that a 1% reduction in the number of suppliers leads to a 0.6% increase in marginal costs. I show how comparable effects can be obtained through premium subscriptions to digital platforms.

This paper is related to the vast literature on the increase in market power and its sectoral heterogeneity. Grullon, Larkin, and Michaely (2019), Gutiérrez and Philippon (2019), Autor et al. (2020) and De Loecker et al. (2020) attribute the increase in concentration and markups to the rise of superstar firms, although their evaluation of welfare and competitiveness differ. Regarding the heterogeneity across sectors, Valentinyi and Herrendorf (2008), Brynjolfsson, McAfee, Sorell, and Zhu (2008), Elsby, Hobijn, and Şahin (2013), Karabarbounis and Neiman (2014), Eden and Gaggl (2018), Bajgar, Criscuolo, and Timmis (2021), Firooz, Liu, and Wang (2022) and Kwon, Ma, and Zimmermann (2023) show that the increase in concentration and/or the decline in the labor share is sector-specific, and that they correlate with the investment in automation, robots or IT technologies. Bessen (2017), Calligaris, Criscuolo, and Marcolin (2018), Bijnens and Konings (2018), Crouzet and Eberly (2019) and Crouzet and Eberly (2021), Diez, Fan, and Villegas-Sánchez (2019), Akcigit et al. (2021) and Markiewicz and Silvestrini (2022) extend these findings to sectoral markups and business dynamism. The majority of the papers employ an empirical approach, while I present a theoretical framework, which proposes the rise of e-commerce platforms as a novel explanation for the observed trends.

Although, in this paper, the core of the analysis is firms' subscription to the platforms and not the platforms themselves, nor their optimization strategy, it is worth to refer to the long-standing tradition on platform theory: Rohlfs (1974), Katz and Shapiro (1985), Katz and Shapiro (1994), Farrell and Katz (1998), and, in particular, Rochet and Tirole (2003), Armstrong (2006), Rochet and Tirole (2006) and Edelman and Wright (2015). The differences between online and offline transactions, as well as the gains from e-commerce, are discussed in Brynjolfsson and Smith (2000a), Brynjolfsson and Smith (2000b), Brynjolfsson, Hu, and Simester (2011), Hortaçsu and Syverson (2015), Cavallo (2017) and Cavallo (2018). Finally, Gutierrez (2021) presents a welfare evaluation of Amazon, while studying its business model and role as both intermediary and market-maker, and Farronato, Fradkin, and MacKay (2023) test whether Amazon engages in self-preferencing to favor its own products. In the model I present, platforms' strategies are greatly simplified to gain in tractability.

The remainder of the paper proceeds as follows. Section 2 shows the rise of market power and e-commerce platforms use in the data, and their heterogeneity across sectors and firms. Section 3 introduces the theoretical model, while Section 4 studies the role of platform shocks for market power outcomes. Section 5 presents the main experiment, in which I quantify the impact of platforms on the observed trends in markups and concentration. Section 6 describes the extent of shocks propagation through the I-O structure, and Section 7 the analysis on sectoral heterogeneity. Section 8 concludes.

2 Empirical Evidence

In this section, I discuss the motivating evidence for the paper: the first subsection describes market power dynamics at different levels of aggregation. The second subsection presents the rise of intermediary e-commerce platforms, as well as the heterogeneity in their uptake across sectors and firms.

2.1 Increase in Market Power

To study the increase in market power in the US economy, I use Compustat data. The data covers publicly listed firms at the yearly frequency and contains information from the balance sheet of the companies.[7] For the purpose of this study, I focus on the time frame from 1990 to 2016, as it starts right before e-commerce platforms began to operate in the mid-nineties. Sectors are defined at the NAICS-2 level of granularity and, then, further aggregated to obtain the 14 macro-sectors described in the Bureau of Economic Analysis (BEA) Input-Output tables.

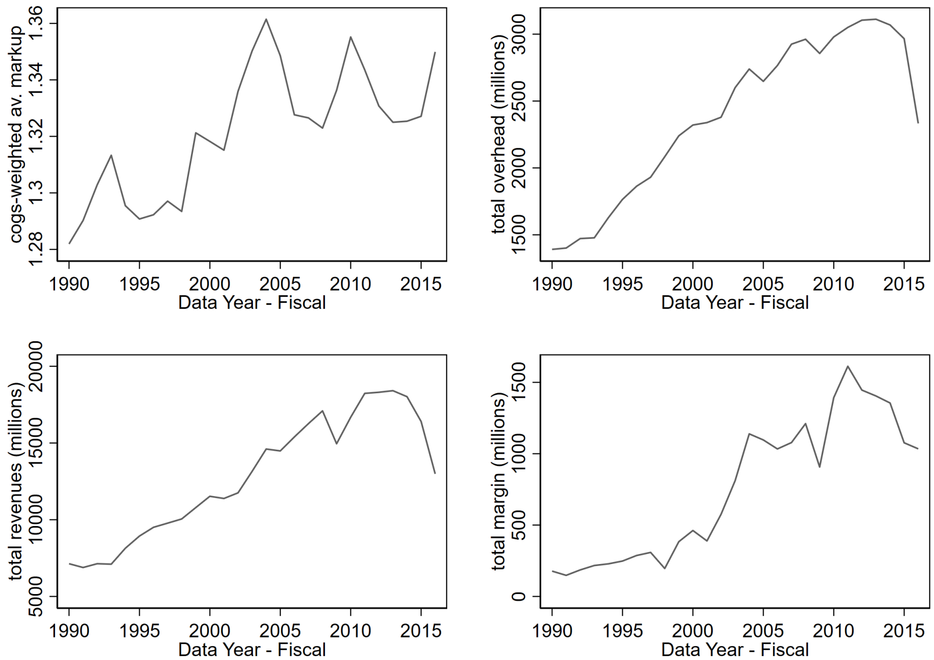
Figure (1) displays the aggregate markup, the total overhead expenditure, computed as the sum of administrative expenses, the total revenues, and the operative margins. All nominal series are deflated. Margins are defined at the aggregate level as total revenues minus total variable costs, where the latter equals, under profits maximization, the revenues themselves divided by the aggregate markup, minus total overhead costs. As a robustness exercise, Appendix B reports the results for aggregate profits.

Markups are estimated following the methodology outlined in De Loecker et al. (2020), which is based on the seminal work by Hall (1986). Assuming that firms minimize their costs by optimally adjusting a bundle of inputs with different degrees of flexibility, the ratio between prices and marginal costs, i.e. the firm-level markup, reduces to a product between two quantities: the inverse of the revenue share of the variable inputs and the elasticity of the variable inputs to output. The existence of inputs that cannot be adjusted in the short-run is key for the analysis, as it resembles the assumptions in the theoretical model. For consistency, Appendix A presents six alternative measures for the markup, while Figure (1) reports only the baseline.[8]

[7] De Loecker and Eeckhout (2018) and Markiewicz and Silvestrini (2022) present evidence for other developed economies.

[8] In the replication package, I collect 18 alternative measures, hence the number used to identify each

Figure 1: Aggregate Markup, Overhead Costs, Revenues and Margins



Notes: The graph plots the evolution of the cost-weighted aggregate markup, of the total overhead expenditure (computed as the sum of the total administrative expenses for each year, $XSGA$ in Compustat), of the total revenues (sum of $REVT$), and of the operative margins. The time horizon is 1990:2016; all nominal series are deflated.

Once markups are estimated at the firm-level, they are aggregated using a cost-weighted average, where the weights are represented by the ratio between the firm-level and the total costs of goods sold. I use this functional form as it represents the welfare-relevant measure from the theoretical model.[9] Moreover, van Vlokhoven (2021) shows that the increase in sales-weighted markups estimated in Compustat is driven by measurement error, while the cost-weighted average is a more robust measure of market power.

As confirmed by Figure (1), markups increased over the sample. Appendix A shows that levels and growth rates strongly vary depending on the specification. In particular, markups are significantly smaller if administrative expenses are factored in, consistently with Traina (2018). Nonetheless, they always display a positive trend, no matter the measure considered. Autor et al. (2020) claim that market concentration presents a similar

specification in Appendix A. These differ in the estimation of the elasticity and in the definition of the variable input share, e.g. by using a bundle of materials and labor, or by including administrative expenses.

[9]The aggregator from the model pins down the functional form of the aggregate/sectoral markups. In this framework, it implies that the sectoral markups are cost-weighted averages of the firm-level markups, or, equivalently, revenue-weighted harmonic averages, see Edmond, Midrigan, and Xu (2018).

Figure 2: Correlation Markups and Overhead Costs

Notes: The graph plots the evolution of the correlation between firm-level markups and administrative expenses, used as a proxy of overhead costs, over the horizon 1980:2016. The left panel displays the correlation with respect to the overhead cost share over total costs, while the panel on the right with respect to overhead costs in level.

pattern. The second panel of Figure (1) demonstrates that the overhead spending is trending upward, but the revenues are increasing as well: the increase in markups and revenues is large enough for the margins to grow, meaning that overhead costs are more than compensated. In other words, market power is rising.

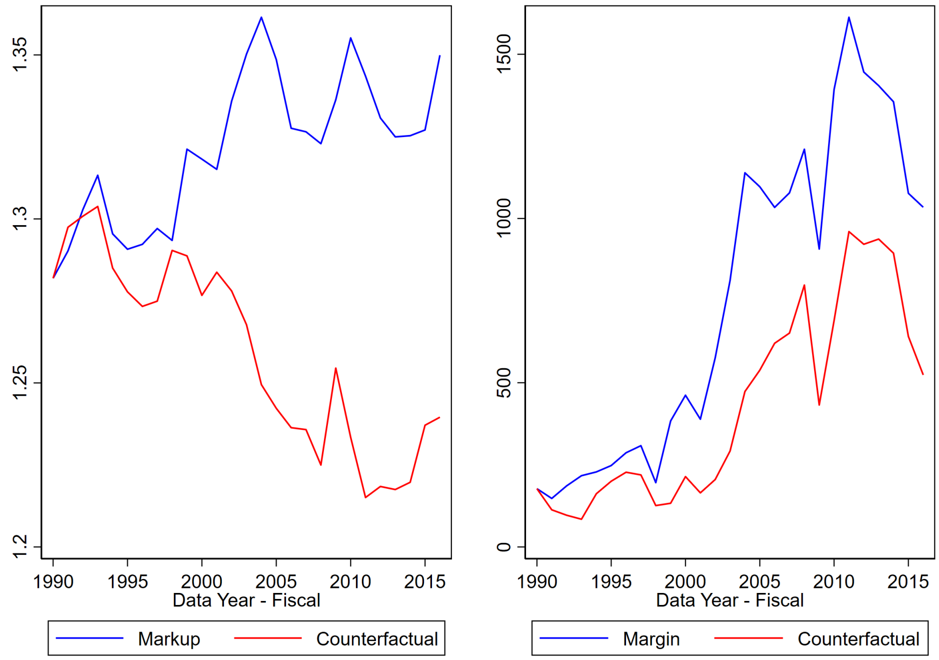
Still, part of the increase in markups might come mechanically from a change in the cost structure of the firms: with an increase in fixed costs, firms need larger markups to break-even, as claimed by Bridgman and Herrendorf (2021).[10] This is exactly the pattern observed in the US, as shown by Figure (1). Thus, it is not surprising that a positive correlation can be found between firm-level markups and administrative expenses, a proxy for overhead costs, and that the magnitude of the correlation is growing over time, as described by Figure (2).[11]

A simple back-of-the-envelope calculation can be used to disentangle the contribution

[10]Kost, Pearce, and Wu (2019) show that the rise in trademark activities is associated with an increase in market power.

[11]Both these predictions are rationalized by the model from Section 3, where an increase in the investment through the platforms augments overhead spending and allows firms to increase their markups.

Figure 3: Aggregate Markup and Margins, with Counterfactual

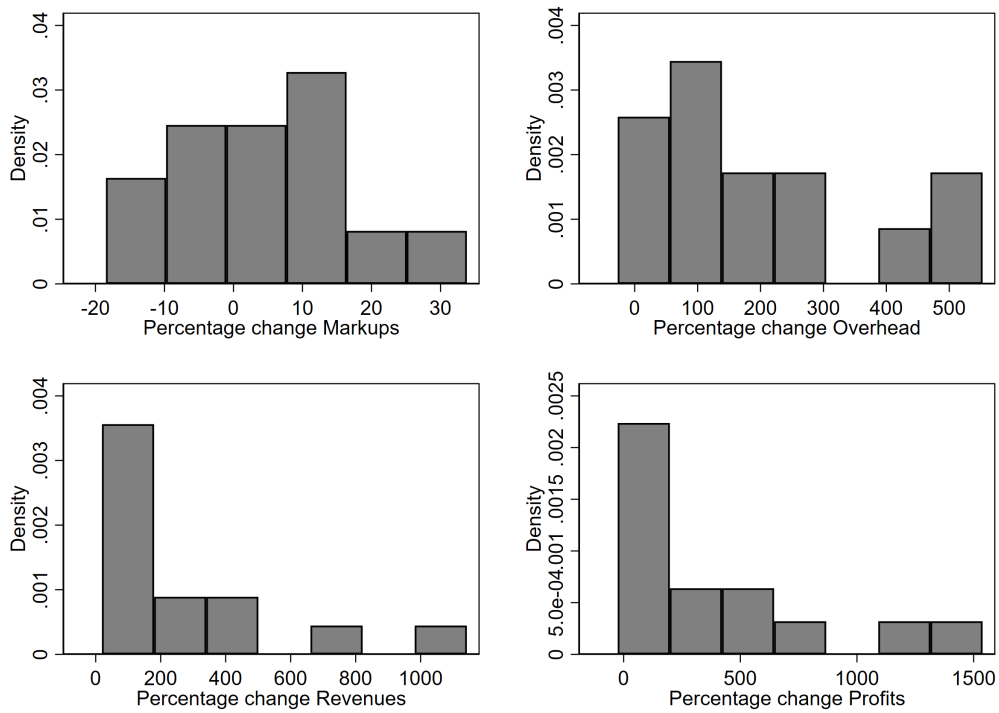


Notes: The graph plots the evolution of the cost-weighted aggregate markup (left panel, blue line) and of the operative margins (right panel, blue line) from Figure (1). The series in red describe two counterfactual experiments. The counterfactual on the left represents a counterfactual markup, computed such that the operative margin is kept constant at the 1990 level. The counterfactual on the right is similar but it displays the margin, taking as given the 1990 aggregate markup. The time horizon is 1990:2016. Data are in millions dollars, deflated.

of overhead costs on markups, showing that the increase in market power survives this decomposition: Figure (3) plots the cost-weighted aggregate markup (left panel, blue line) and the operative margins (right panel, blue line), as computed in Figure (1). The two series are contrasted by two counterfactual experiments, drawn in red. The red line on the left panel represents a counterfactual markup estimated such that the margin is kept constant at the 1990 level. In other words, this is the markup that exactly offsets the trend in overhead expenditure (taking as given the pattern of total revenues). The counterfactual on the right is for operative margins, keeping fixed the aggregate markup at the 1990 level.

Until the year 2000, the counterfactual and the *true* markup move almost 1-to-1: this means that, at least through the lenses of the decomposition, the aggregate markup is moving mechanically to respond to the increase in overhead costs. Results are completely different after the turn of the century, clearly showing that the increase in markups overshoots a mere compensation of overhead costs, confirming the increase in market power. Similar conclusions emerge from the right panel.

Figure 4: Dispersion of Changes in Markups, Overhead, Revenues and Profits across Sectors



Notes: The graph plots the percentage changes between 2016 and 1990 of (i) markups, (ii) overhead costs, (iii) revenues and (iv) profits in 14 NAICS-2 sectors of the US economy. The sectors are, in alphabetical order, 1. Agriculture, 2. Arts and Entertainment, 3. Construction, 4. Education and Health, 5. Finance, Insurance, Real Estate (FIRE), 6. Information, 7. Manufacturing, 8. Mining, 9. Other Services, 10. Professional Services, 11. Retail, 12. Transportation and Warehousing, 13. Utilities, and 14. Wholesale. Markups are estimated at the firm-level with the baseline specification from Figure (1) and, then, aggregated at the sectoral level using a cost-weighted average. The same aggregation is used for profits, while revenues and overhead costs are defined as sums.

Moving to the sectoral dimension, Figure (4) presents the percentage changes between 2016 and 1990 of markups, overhead costs, revenues and profits in 14 NAICS-2 sectors of the US economy. The name of each (macro)sector is reported in the caption of the figure. The methodology for the estimation of firm-level markups follows the one used in Figure (1). Then, markups are aggregated at the sectoral level using a cost-weighted average, where the weights are defined as the share of firm-level costs of goods sold ($COGS$ in Compustat) over the total $COGS$ in a given pair sector-year. The same holds for sectoral profits, while sectoral revenues and overhead costs are defined as sums.

The first panel of Figure (4) shows that sectors are characterized by a stark heterogeneity in markup trends: although the median change is positive, some sectors display a flat, or even decreasing, pattern. Overhead costs, revenues and profits present similar dynamics. Hsieh and Rossi-Hansberg (2023), while focusing on a longer time frame, claim that market concentration is also heterogeneous across sectors. Appendix A plots markup trends for each sector, while Appendix B replicates the same study for sectoral profits.

Due to the restricted number of sectors, it is difficult to rationalize the observed heterogeneity. Still, the sectoral labor share can be informative: sectors characterized by a large labor share should rely less on the platforms, given that intermediates represent a smaller fraction of the variable costs of the firms.[12] In other words, the investment in platforms comes with a lower benefit. If platforms usage exacerbate the increase in market power, these sectors should display a smaller increase in markups with respect to the low-labor, high-intermediate sectors.

Using Bureau of Labor Statistics (BLS) data on the sectoral labor share, I find confirmation for this hypothesis. Sectors characterized by a lower labor share display higher markups on average. Moreover, sectors that presented a stronger decline in the labor share over the last two decades show a sharper increase in markups: regressing the percentage change in sectoral markups from 2016 to 1990 on the percentage change in the sectoral labor share, the coefficient is -0.16, with a *p-value* of 0.049. Consistently with this mechanism, sectors with a stronger increase in the sectoral overhead expenditure are characterized by a larger increase in markups, although not statistically significant.

To directly test the mechanism, I exploit sparse sectoral data on platforms use. According to Thomson's analysis on Amazon Web Services, presented in the subsection below, the top 10 sectors in terms of Amazon subscribers are Computer Software, Retail, Real Estate, IT and Services, Hospitals and Healthcare, Marketing and Advertising, Internet, Insurance, Financial Services and Credit Unions.

I proceed as follows: first, I define for each NAICS-3 sector of the US economy two dummy variables that represent intensive use of platforms. The first dummy takes the value 1 when the NAICS-3 industry belongs to a NAICS-2 sector which contains one of the top 10 sector mentioned above. The second dummy equals 1 whenever the NAICS-3 sector itself is a top 10 platform user. Then, I regress either the sectoral markups from 2016 in levels or the change in sectoral markups from 2016 to 1990 in percentage points on one of the dummy. Results are shown in Table (1).

Table (1) shows that results are economically relevant: sectors characterized by intensive use of digital platforms display a sectoral markup that is higher by almost 0.5 on average. Moreover, the growth rate of the sectoral markups in these sectors is approximately 30% higher, although this second result is not statically significant.

[12] Instead of the intermediate input share, I use the inverse of the labor share since (i) it is difficult to separate capital and intermediates in the data and (ii) they are equivalent in the model. From Valentinyi and Herrendorf (2008), the intermediate share is higher in Agriculture and Manufacturing than in Services.

Table 1: **Sectoral Markups and Sectoral Platforms Use**

	NAICS-2	NAICS-3
$\mathcal{M}_k$	0.47*	0.44*
$\Delta\mathcal{M}_k$	26.37	32.36
Number of Observations:		90

Notes: The table presents the regression coefficients for four specifications: (i) sectoral markups regressed on a dummy for NAICS-2 sectors with intensive use of platforms (top left), (ii) sectoral markups on a dummy for NAICS-3 sectors with intensive use of platforms (top right), (iii) percentage change in sectoral markups on dummy for NAICS-2 sectors (bottom left), (iv) percentage change in sectoral markups on dummy for NAICS-3 sectors (bottom right). Regressions in levels are for 2016, while on 2016-1990 differences for the percentage variations, and refer to NAICS-3 sectors. Stars represent 5% significance.

2.2 Increase in Digital Platforms Use

Over the last two decades, firms increased their use of digital intermediary platforms: in 2019, the share of *B2B* sales via e-commerce platforms over the total *B2B* sales in the US was 13%, while the projection for 2023 is 17%, as estimated by Statista. In terms of value, US *B2B* digital sales are expected to surpass 1.5 trillion dollars in 2023, which represents more than 5% of the American GDP.[13]

Platforms are beneficial to firms in two ways. First, firms can enjoy a direct reduction of inputs costs, e.g. through special discounts on Alibaba Plus or by saving on recurring purchases with Amazon Business Prime. Second, firms benefit indirectly thanks to the improvement of processes like logistic or warehousing, as with Amazon Web Services. Joining a platform comes at a cost and entails two choices: (i) whether to enter the platform and (ii) whether to adhere to a wider range of services offered by the platform.[14] In this section, I discuss the empirical relevance of these dynamics, using Amazon and Alibaba as leading examples.

Alibaba gathers more than 40 millions users globally, with almost a million of paying premium members. Alibaba offers both generalist and specialist marketplaces, ranging from manufactured products to machinery, food and raw materials. Premium services are targeted to both buyers and sellers: sellers can subscribe to Alibaba Basic, Premium or Plus for advertisement and stronger indexation, while buyers can access the Benefits Program, which allows them to lower their input costs thanks to the access to a large network of low-cost sellers.[15]

[13]This pattern is aligned with historical trends: in the US, half of the transactions for manufactured goods were intermediated by wholesalers in 2012, significantly more than the 32% from 1992. Three quarters of the increase are driven by the top 1% wholesalers, see the discussion in Ganapati et al. (2018).

[14]De Fiore et al. (2023) discuss how fees range from *entry* fees to get access to the platform to subscription fees for premium use. Moreover, Boissay, Ehlers, Gambacorta, and Shin (2021) claim that the fee structure of e-commerce platforms is responsible for approximately one third of their revenues.

[15]For instance, through the *Request for Quotation* service buyers can post a precise description of a

Similar dynamics exist for Amazon Business Prime. As claimed in a survey by Statista, Amazon Business is the most popular *B2B* generalist marketplace in the US, with 36% of *B2B* buyers using it currently or in the past, followed by eBay and Alibaba, at 30% and 27%, respectively. Amazon Business Prime presents several subscription levels, whose benefits are quantitatively relevant: the economic report by Forrester (2020) claims that firms can cut their costs by approximately 10% over three years by switching to Amazon Business stores.[16] More in general, this aligns with the fact that prices are 9-16% lower online than in physical locations, see the evidence in Brynjolfsson and Smith (2000a).

In addition to this direct reduction of purchasing prices, platforms use can also lower the variable costs of the firm indirectly through efficiency gains. This second dimension regards the improvement of managerial processes, in line with the results in Bender, Bloom, Card, Van Reenen, and Wolter (2018). Amazon represents a good example for these efficiency gains, both through Amazon Business Prime and, more importantly, Amazon Web Services (AWS).

AWS provides services related to computing, storage, database, networking and analytics. Subscribers can participate to the AWS Partner Network, a global network with more than $100,000$ partners that share expertise and resources, and AWS Marketplace, a digital catalog of data products and software. I use AWS as a reference given its leadership in the market for cloud services: AWS has a clear advantage in terms of infrastructure, with more than five times the servers of its next 14 competitors combined, and it accounts for 41.5% of the cloud market, more than Microsoft, Google, and Rackspace combined.

Amazon Web Services usage displays a strong heterogeneity between sectors, with firms from Retail, Computer Software, IT, Real Estate and Healthcare as the main users.[17] A similar pattern can be uncovered for Amazon Business Prime, where the packages offered target few selected industries. Regarding the subscribers of Amazon Web Services, several Fortune 500 firms and almost all of the Fortune 100 are AWS Partners. Still, due to the number of features and bundles offered, Amazon is able to serve a diverse pool of customers, from young startups to large enterprises.

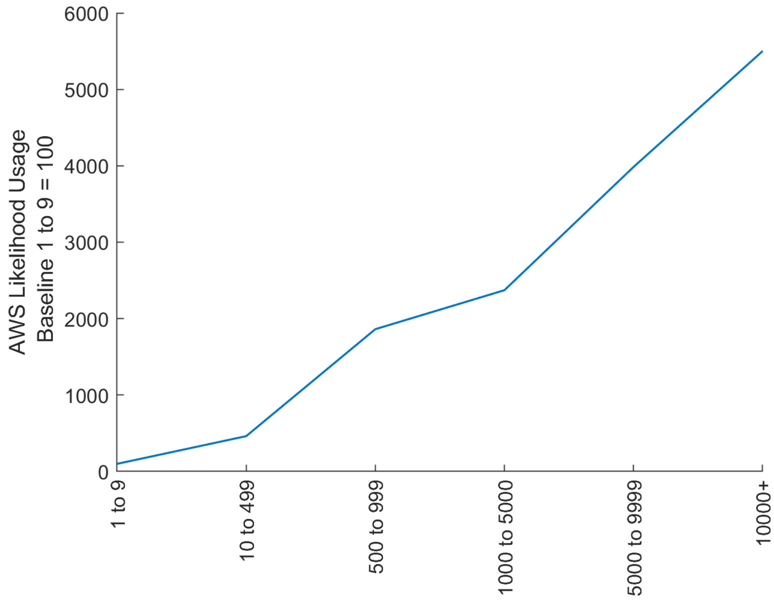
The total number of AWS global users is around 1.5 millions, of which almost 600 thousands in the US: this represents almost 15% of the active firms in the US from the Business Dynamics Statistics (BDS). Within active subscribers, there is a strong heterogeneity in terms of firms size: comparing the distribution of subscribers with the empirical firm size

product and let suppliers bid for the price.

[16] Firms can lower their costs as: (i) buyers can leverage lower prices by shifting to similar, but cheaper, items, (ii) buyers get recommendations and special discounts directly from Amazon, and (iii) buyers enjoy free shipping on selected products, or for eligible orders over a certain threshold.

[17] Precisely, the number of subscribers is: Computer Software $147,726$, Retail $129,829$, IT and Services $77,779$, Hospitals and Healthcare $62,444$, and Real Estate $78,103$.

Figure 5: Amazon Web Services Usage, Likelihood per Size Bin



Notes: The graph plots the likelihood of being an AWS subscriber for each bin of the firm size distribution. For the US, the number of firms in each size bin comes from BDS, while the global number of AWS subscribers from Thomson data. Given the misalignment between data sources, results hold qualitatively under the assumption that the shape of the distribution of global AWS users is informative for the US as well. The likelihood of being an AWS user is represented as a multiple of the baseline likelihood for firms with 1 to 9 employees, normalized to 100.

distribution from BDS, a positive correlation between size and usage can be found.[18] This is shown in Figure (5), which plots the likelihood of finding a subscriber for each size bin.

Finally, data in the economic report by Intricately (2022) show both the extensive and the intensive dimensions in the use of digital platforms. Although three quarters of AWS users spend less than 1000 dollars per month in subscription fees, 15% is close to 5 thousands, while the top 2.5% is above 100 thousands per month, with largest spenders surpassing 1 million.[19] Moreover, 85% of AWS subscribers are present on Amazon Web Services only, while the remaining firms present multi-cloud adoption, since they also use Azure, GCP or Oracle. Not surprisingly, there are strong differences in multi-clouding strategies across size bins: despite only 22% of startups, 20% of medium firms and only

[18]In levels, global AWS users for the 1 to 10 employees size bin are $362,199$, for 10-50 employees $288,488$, for 50-200 employees $178,120$, for 200-500 employees $37,664$, for 500-1000 employees $18,452$, for 1000-5000 employees $19,670$, for 5000-10000 employees $5,182$, and, finally, for firms with more than 10000 employees the number of users is $6,272$. As above, data come from Thomson, available at https://www.thomsondata.com/customer-base/companies-that-use-aws.php.

[19]A similar dispersion can be found for Amazon Business Prime, where subscriptions go for few tens of dollars to thousand of dollars, reaching even 100 thousands, when factoring in installation and integration expenses, see Forrester (2020).

10% of small business are using multiple platforms, 77% of large enterprises are multi-users. Still, the percentage of firms using a multi-cloud strategy has grown significantly across all company sizes in the last years.

To conclude, a summary of the findings of Section 2 follows. At the aggregate level, the rise of markups goes together with the rise of e-commerce platforms. Overhead costs increased as well, but not enough to fully justify the growth in markups, as also suggested by the concurrent increase in profits and concentration. Regarding the sectoral dimension, there is heterogeneity in market power outcomes, which can be rationalized by how much sectors rely on platforms. Because of their nature, platforms usage displays heterogeneity across sectors but also across firms, both extensively and intensively.

3 The Model

The model is inspired by Atkeson and Burstein (2008), and it features the supply side only. The framework presents oligopolistic competition and I-O linkages, which are modelled following Grassi (2017), while the investment decision resemble the one in De Ridder (2019).[20] The model is further augmented with two-way firm heterogeneity in productivity and implementation costs.[21]

3.1 I-O Structure and Platforms

The economy features a finite and given number of sectors N, each one populated by a countable number of firms N_k. Sectors are indexed by the subscript $_k$. Within sectors, firms produce differentiated goods and compete under oligopolistic competition à la Cournot. Each individual variety y_{ikt}, produced by firm i in sector k and period t, is aggregated into composite goods by sectoral bundlers, under the following C.E.S. aggregator:

$$Y_{kt} = \left[\sum_{i=1}^{N_k} \left(y_{ikt} \right)^{\frac{\theta-1}{\theta}} \right]^{\frac{\theta}{\theta-1}},$$

where $\theta > 1$ represents the elasticity of substitution between goods.[22]

[20]For tractability reasons, the I-O structure is taken as exogenous by the firms. The assumption can be justified by the broad definition of sectors used in the empirical studies (NAICS-2).

[21]Productivity and implementation costs are drawn upon birth from two uncorrelated distributions. For the relevance of *ex ante* heterogeneity, see Pugsley, Sedláček, and Sterk (2020). By modelling two sources of heterogeneity, the one-to-one correspondence between productivity and market power breaks.

[22]To ease notation, here θ is the same in all sectors. In Section 5, I allow this elasticity to be time and sector-specific when calibrating the model. The same is true for several other parameters of the model, for which, in this section, I drop the time subscript for convenience.

In the following, I refer to sectoral bundlers as *platforms*. Platforms have two roles. First, they pool goods together to create sectoral products, to be used as intermediate inputs. Second, they act as intermediaries, providing marketplaces that connect buyers and sellers across different sectors. Sectoral production Y_{kt} is aggregated into a final good by an aggregate bundler, which operates the following Cobb-Douglas technology:

$$Y_t = \gamma_Y \prod_{k=1}^{N} Y_{kt}^{\beta_k},$$

where γ_Y represents a normalization constant and β_k the expenditure share of the sectoral good from industry k.[23] The aggregators, together with the profit maximization problems of the platforms, imply demand constraints that are internalized by the firms.[24] These conditions define the sectoral prices P_{kt} and the price index P_t.[25]

In this model, I differentiate between two alternative scenarios. Each scenario focuses on one of the two sources of benefits coming from the subscription to the platforms, as identified in subsection 2.2. Several equilibrium conditions are shared by the two scenarios; whenever this is not the case, I name equations using labels a or b, as for equations (1a) and (1b) below, to highlight the key differences between the two models. The first scenario, to which I refer using label a for *Amazon Web Services*, models the indirect benefits of the investment in the platforms. These are efficiency gains, originating from the improvement of managerial practises such as logistic and warehousing, which augment production.

The production function of the firm is a Cobb-Douglas with constant return to scale in labor l_{ikt} and intermediates x_{ikt}^j, similar to Grassi (2017).[26] The underlying I-O structure is directly embedded in production: any firm i uses a bundle of sector-specific intermediates. Each intermediate input of production x_{ikt}^j represents a fraction of the sectoral output Y_{jt}, which is produced by the firms operating in sector j and bundled by the platforms.[27]

[23] Note that $\gamma_Y = \prod_{k=1}^{N} \beta_k^{-\beta_k}$.

[24] Sectoral and aggregate bundlers maximize profits under perfect competition, as price-takers. Despite this, the profits of the platforms are non-zero, since they receive the subscription fees from the firms. Still, their maximization problem is not fully formalized in this paper: the scope of the paper is to study the market power outcomes of the firms investing through the platforms, not the strategies of the platforms themselves. For the latter, see, for instance, Gutierrez (2021) and Kang and Muir (2022).

[25] Where $P_t = \prod_{k=1}^{N} P_{kt}^{\beta_k}$ and $P_{kt} = \left[\sum_{i=1}^{N_k} (p_{ikt})^{1-\theta}\right]^{\frac{1}{1-\theta}}$.

[26] The constant return to scale assumption implies that the input elasticities α_K and ω_{Kj} satisfy: $\alpha_K + \sum_{j=1}^{N} \omega_{Kj} = 1$ for any sector k.

[27] This implies that $x_{ikt}^j = \left[\sum_{l=1}^{N_j} \left(x_{ikt}^j(l)\right)^{\frac{\theta-1}{\theta}}\right]^{\frac{\theta}{\theta-1}}$, where $x_{ikt}^j(l)$ is the quantity produced by firm l in sector j that is used as intermediate input for the production of variety i in sector k. Moreover, $Y_{jt} = \sum_{k=1}^{N} \sum_{i=1}^{N_k} x_{ikt}^j$, see Grassi (2017) for details.

Hence, firm-level production y_{ikt} is:

$$y_{ikt} = \zeta_{KY} \left(\frac{a_{ikt}}{s_{ikt}} \right) (l_{ikt})^{\alpha_K} \prod_{j=1}^{N} \left(x_{ikt}^{j} \right)^{\omega_{Kj}} , \tag{1a}$$

where ζ_{KY} is a normalization constant.[28] a_{ikt} is the idiosyncratic Total Factor Productivity (TFP), drawn once upon birth from a known distribution function, while $s_{ikt} \in (0, 1]$ represents the benefits of subscribing to the platforms. Whenever s_{ikt} is equal to 1, the firm is not subscribed to the platform, while the larger the investment is, the *lower* s_{ikt} becomes, i.e. s_{ikt} gets closer to zero.

In the second specification, b for *(Amazon) Business Prime*, the benefits of the subscription are modelled on the cost-side. This second scenario poses the emphasis on the immediate benefit of the investment through the platforms, which entails the direct reduction of input prices. In this scenario, s_{ikt} represents the fraction of the variable costs that is not abated by the firms. Here, the production function is:

$$y_{ikt} = \zeta_{KY} a_{ikt} (l_{ikt})^{\alpha_K} \prod_{j=1}^{N} \left(x_{ikt}^{j} \right)^{\omega_{Kj}} . \tag{1b}$$

In the following, I show that the two scenarios are virtually equivalent, as they deliver the same distribution of markups, marginal costs and market shares. Still, subscribing to the platforms has different implications in the two specifications, given that, under scenario a, it improves the efficiency of the firm.[29] Thus, results for aggregate productivity are different: I discuss these findings in subsection 3.4.

To keep to model simple, without compromising the key features of the mechanism, s_{ikt} appears on the production or costs side linearly. A discussion on this assumption, and on the connection with alternative specifications in which s_{ikt} is modelled non-linearly, is presented in Appendix C. Finally, due to the presence of both firm-level productivity and investment, this model generalizes a wide class of frameworks.[30]

3.2 Second Stage

In this framework, firms act sequentially: in the first stage, firms choose s_{ikt} to optimize their investment strategy. In the second stage, taking s_{ikt} as given, firms maximize their

[28] Note that $\zeta_{KY} = \alpha_K^{-\alpha_K} \prod_{j=1}^{N} \omega_{Kj}^{-\omega_{Kj}}$ for each sector k.

[29] More in general, in this case s_{ikt} could be considered as the *observable* part of productivity, which is related to efficiency, with a_{ikt} representing the residual share. Firms can affect the first by investing in the improvement of management processes, consistently with Bender et al. (2018) and Bruhn, Karlan, and Schoar (2018).

[30] If the subscription phase is removed, the model reduces to a standard oligopolistic competition model with an I-O structure, as in Grassi (2017), while if TFP equals a constant, all the variation in firms' performances comes from the distribution of investment, as in De Ridder (2019).

profits. I solve this problem using backward induction, starting from the second stage. Firms minimize their total costs subject to the technological constraint, and this task differs depending on the scenario considered. In scenario a, this implies:

$$\min_{l_{ikt}, x^j_{ikt}} W_t l_{ikt} + \sum_{j=1}^{N} P_{jt} x^j_{ikt} + F^x_{ikt}, \tag{2a}$$

such that equation (1a) holds, and where W_t represents the nominal wage in the economy.[31] In scenario b, firms minimize:

$$\min_{l_{ikt}, x^j_{ikt}} s_{ikt} \left(W_t l_{ikt} + \sum_{j=1}^{N} P_{jt} x^j_{ikt} \right) + F^x_{ikt}, \tag{2b}$$

subject to equation (1b). In Appendix C, I present an alternative model where s_{ikt} scales the intermediate input costs, but not the wage bill, showing that results are consistent.

Nominal overhead costs F^x_{ikt} are a function of s_{ikt}, and they represent the subscription fees: the investment in the platforms results in subscription costs that are paid *ex ante*, no matter how much the firm is producing in the second stage. Thus, the subscription fees are taken as given in the cost minimization problem. Moreover, as in De Ridder (2019), firms incur in these costs in every period they operate.[32]

Combining the F.O.C.s for the different inputs, I can show that, under both scenarios, the total costs can be rewritten as $\lambda_{ikt} y_{ikt} + F^x_{ikt}$, where λ_{ikt} is the firm-specific Lagrange multiplier from the cost minimization problem. Thus, idiosyncratic nominal marginal costs MC_{ikt} are identified by the Lagrange multiplier. Solving for λ_{ikt}, marginal costs are:

$$MC_{ikt} = \frac{s_{ikt}}{a_{ikt}} W_t^{\alpha_K} \prod_{j=1}^{N} P_{jt}^{\omega_{Kj}} \equiv \frac{s_{ikt}}{a_{ikt}} \Xi_{kt}, \tag{3}$$

where Ξ_{kt} is the short-hand notation for the sectoral component of the marginal costs.

Equation (3) shows, through s_{ikt}, the benefits of subscribing to the platforms: no matter if gains are modelled on the production or on the cost side, the investment leads to a uniform abatement of marginal costs.[33] The *ex post* heterogeneity in firm performances, driven by the underlying distribution of marginal costs, is explained by both the

[31] Given the Cobb-Douglas aggregator, I assume that firms have limited ability in computing (and internalizing) the effects of their choices on the quantities outside their sector, see Grassi (2017). Note that output markets are oligopolistic, while the labor market is competitive

[32] This resembles a standard subscription model, as AWS or Alibaba Premium, in which firms pay fees monthly, or yearly, to continue to enjoy the services offered by the platforms. Moreover, these recurrent costs are in line with the high depreciation rate of software, see Li and Hall (2020).

[33] More in general, s_{ikt} can be considered as a proxy for the ability of the firm to build better links with its suppliers, which allows the first to decrease the price of its inputs (and extract more rents).

productivity dispersion and the different investment behavior. By considering the latter as a proxy for the quality of the network each firm operates in, the dualism echoes the empirical findings in Bernard, Dhyne, Magerman, Manova, and Moxnes (2022).

Firms compete under Cournot oligopolistic competition: each firm maximizes its nominal profits by selecting the optimal quantity y_{ikt}, internalizing the effects of this choice on sectoral variables. The constraints of the maximization problem come from the cost minimization problem above, and from the definition of aggregate and sectoral demands. Profits d_{ikt} are defined as nominal revenues, $p_{ikt}y_{ikt}$, net of total costs, as outlined in (2a) and in (2b). In both scenarios, firms maximize:

$$\max_{y_{ikt}} p_{ikt}y_{ikt} - \frac{s_{ikt}}{a_{ikt}}\Xi_{kt}y_{ikt} - F^x_{ikt},$$

subject to:

$$y_{ikt} = \left(\frac{p_{ikt}}{P_{kt}}\right)^{-\theta} Y_{kt} = \left(\frac{p_{ikt}}{P_{kt}}\right)^{-\theta} \beta_k \left(\frac{P_{kt}}{P_t}\right)^{-1} Y_t,$$

where p_{ikt} is the individual price, and the demand constraint comes from the maximization problems of the sectoral and aggregate bundlers. From the F.O.C., I can solve for the optimal nominal price as:

$$p_{ikt} = \left(\frac{\theta}{\theta-1}\right)\left(\frac{1}{1-q_{ikt}}\right)\frac{s_{ikt}}{a_{ikt}}\Xi_{kt} = \mu_{ikt}\frac{s_{ikt}}{a_{ikt}}\Xi_{kt}, \tag{4}$$

where q_{ikt} represents the market share of the firm, $q_{ikt} \equiv \frac{p_{ikt}y_{ikt}}{P_{kt}Y_{kt}} = \left(\frac{p_{ikt}}{P_{kt}}\right)^{1-\theta}$, and μ_{ikt} the idiosyncratic markup, which is increasing in q_{ikt}. Note that, when $q_{ikt} \to 0$, the markup converges to the monopolistic competition markup $\theta/(\theta-1)$, since the firm is atomistic. Finally, profits d_{ikt} can be rewritten as net revenues minus overhead costs:

$$d_{ikt} = \left(1 - \frac{1}{\mu_{ikt}}\right) p_{ikt}y_{ikt} - F^x_{ikt}. \tag{5}$$

3.3 First Stage

In the first stage, firms choose the optimal investment strategy s_{ikt} to maximize profits.[34] The subscription fee f^x_{ikt}, the real counterpart of F^x_{ikt} used above, is modelled using an increasing and convex function from De Ridder (2019):

$$f^x_{ikt} = \frac{\nu_{kt}}{\phi_{ikt}}\left[\left(\frac{1}{s_{ikt}}\right)^{\psi_{kt}} - 1\right].$$

[34] Following the empirical results on matching propensity and buyer density in Miyauchi (2018), I assume that the investment behavior has no direct effects on other buyers' investment, and that there are no strategic interactions in the investment choice.

The function is decreasing in s_{ikt}: a larger investment in the platforms, resulting in s_{ikt} closer to zero, leads to higher fees f^x_{ikt}. In addition, the function implies that there are no costs if the firm is not subscribed to the platform, i.e. when $s_{ikt} = 1$, while $f^x_{ikt} \to \infty$ when $s_{ikt} \to 0$, ensuring that a solution exists where all firms have non-zero marginal costs.

Three key quantities scale the investment cost function: costs are disproportionally increasing in ψ_{kt}, linearly increasing in ν_{kt}, and linearly decreasing in ϕ_{ikt}. ϕ_{ikt} captures the observed firm-level heterogeneity in platforms implementation costs. Lower implementation costs foster subscription, leading to larger markups, size and profits.[35] As ϕ_{ikt} and a_{ikt} are the only sources of heterogeneity across firms in a given sector, firms are completely identified by them.[36]

ν_{kt} impacts the first moment of the cost function, and it affects the average investment in the platforms, while ψ_{kt} captures both the first and the second moments of the function, since it describes its curvature. This means that ψ_{kt} disciplines the investment dispersion. The two parameters are allowed to be heterogeneous across sectors and time to capture the sector-specific relevance of the platforms. In the model from Appendix C, the incentives to subscribe to the platforms are sector-specific even if the two primitives are homogeneous across sectors. In the main experiments, these parameters are shocked to study the influence of e-commerce platforms on sectoral and aggregate market power.[37]

The trade-off between overhead and marginal costs that originates has been used to describe processes like R&D, innovation, or acquisition of intangible capital. Recently, De Ridder (2019) and Olmstead-Rumsey (2019) discussed these dynamics in conjunction with market power outcomes. The mechanism I present differs from the above in at least two dimensions: (i) the investment is driven by the need to acquire intermediate inputs, hence the trade-off is sector-specific, and (ii) the subscription directly affects input prices, under scenario b, leaving firm-level TFP unaffected.

Given this functional form, and using the results from the second stage following backward induction, I can rewrite the profit maximization problem in real terms as:

$$\max_{s_{ikt}\in(0,1]} Y_t \beta_k q_{ikt} \left[\frac{1}{\theta} + q_{ikt}\left(\frac{\theta-1}{\theta}\right)\right] - \frac{\nu_{kt}}{\phi_{ikt}}\left[\left(\frac{1}{s_{ikt}}\right)^{\psi_{kt}} - 1\right], \tag{6}$$

where q_{ikt} is an implicit function of s_{ikt}. The maximization above describes firms' trade-

[35] More generally, this can be considered as a proxy for managerial ability. Recently, several papers linked managerial ability and market power trends, see Ferraro, Iacopetta, and Peretto (2022) and Bao, De Loecker, and Eeckhout (2022).

[36] The two distributions from which firms draw their primitives are assumed to be independent.

[37] A change in Amazon's pricing scheme, for instance a uniform increase in the costs of all the services offered, will be proxied by an increase in ν_{kt}. On the other hand, the launch of a new Alibaba premium membership, on top of the existing subscriptions, can be modelled as a decline in ψ_{kt}, as the shock implies an increase in the investment dispersion.

off in subscribing to the platforms: to lower s_{ikt} and reduce its variable costs, the firm must pay subscription fees. Thanks to the resulting abatement of marginal costs, the firm can diminish its price p_{ikt}, see equation (4), and capture a larger market share q_{ikt}. This leads to a higher markup μ_{ikt} and a larger margin, represented by the first term in the maximization.[38] The benefit of the investment is scaled upward by the relative size of the firm in the sector, q_{ikt}, by the relative size of the sector in the economy, β_k, and by the size of the economy itself, Y_t. The F.O.C. can be written as:

$$s_{ikt} = \min\left\{1, \left(\frac{\nu_{kt}\psi_{kt}}{\phi_{ikt}}\right)^{\frac{1}{\psi_{kt}}} \left(\frac{1}{Y_t\beta_k}\right)^{\frac{1}{\psi_{kt}}} \left[\frac{1+q_{ikt}(\theta-1)}{\left(\frac{1}{\theta}+2q_{ikt}\frac{\theta-1}{\theta}\right)q_{ikt}(\theta-1)(1-q_{ikt})}\right]^{\frac{1}{\psi_{kt}}}\right\}. \quad (7)$$

Through equation (7), I can express s_{ikt} as a function of only one idiosyncratic choice variable, q_{ikt}. Since q_{ikt} itself can be written as a function of s_{ikt} and sectoral quantities, using the definition of the market share together with equation (4), the two equations can be combined to solve numerically for the equilibrium.

The optimal s_{ikt} is increasing in both ν_{kt} and ψ_{kt}, as higher subscription fees lower investment, while it is decreasing in ϕ_{ikt}, given that lower implementation costs lead to more investment in the platforms. Moreover, s_{ikt} is decreasing in the GDP of the economy, Y_t, and in the sectoral market share, β_k, as the two scale up the benefits of the subscription. Finally, the optimal investment is increasing in the market share q_{ikt}, which also implies that s_{ikt} is decreasing in a_{ikt}.[39] This happens as larger firms can dilute, and sustain, higher overhead costs over their scale of production. This is true both in the model and in the data, see Forrester (2020).

These findings state a clear relationship within the model: highly productive firms are larger and charge higher markups, consistently with the empirical evidence in De Loecker et al. (2020). Moreover, they can expand further and impose even higher markups thanks to the larger investment in the platforms they can sustain. This creates a positive correlation between markups and overhead costs, consistently with the results presented in Section 2. Appendix D confirms the intuition by showing the partial derivatives from the model, and how they change in relation to the two sources of firm heterogeneity.

[38] Indeed, the term in the first square brackets is the (gross) profit share $1 - 1/\mu_{ikt}$.

[39] This is true provided that the market share is below 50%, which is satisfied in virtually all the sectors and scenarios I consider.

3.4 Measures of Market Power

In this subsection, I derive analytical expressions for sectoral and aggregate measures of market power and welfare. By definition, the Herfindal-Hirschman Index (HHI) is:

$$HHI_{kt} = \sum_{i=1}^{N_k} (q_{ikt})^2 .$$

Regarding the sectoral markup, I start by deriving the sectoral productivity, following the approach outlined in Edmond et al. (2018). Under scenario a, it is useful to define first an *effective* productivity $z_{ikt} \equiv \frac{a_{ikt}}{s_{ikt}}$. In this scenario, the subscription to the platforms is productive, as it brings efficiency gains: this justifies the definition. The sectoral effective productivity Z_{kt} is the one that satisfies:

$$Y_{kt} = Z_{kt}\zeta_{KY} (L_{kt})^{\alpha_K} \prod_{j=1}^{N} \left(X_{kt}^j\right)^{\omega_{Kj}}$$

where L_{kt} and X_{kt}^j represent, respectively, the total amount of labor and intermediate input from sector j used in sector k.[40] Using the F.O.C.s from the cost-minimization problem, it can be shown that the sectoral effective productivity is a weighted harmonic average of the idiosyncratic effective productivity, where the weights are the firm-level output shares:

$$Z_{kt} = \left(\sum_{i=1}^{N_k} \frac{1}{z_{ikt}} \frac{y_{ikt}}{Y_{kt}}\right)^{-1} . \tag{8a}$$

Taking the same approach for scenario b, there is no need to define an effective productivity z_{ikt} here, as the investment affects only the cost-side of the firm, with no effects on efficiency nor on productivity. Hence, the sectoral productivity is:

$$Z_{kt} = \left(\sum_{i=1}^{N_k} \frac{1}{a_{ikt}} \frac{y_{ikt}}{Y_{kt}}\right)^{-1} . \tag{8b}$$

By definition, the sectoral markup $\mathcal{M}_{kt}$ is the one that satisfies:

$$P_{kt} = \mathcal{M}_{kt} \frac{\Xi_{kt}}{Z_{kt}} . \tag{9}$$

Using equation (8a), under scenario a the sectoral markup can be written as a weighted harmonic average of firm-level markups, where the weights are represented by the market shares q_{ikt}:

$$\mathcal{M}_{kt} = \left(\sum_{i=1}^{N_k} \frac{1}{\mu_{ikt}} q_{ikt}\right)^{-1} . \tag{10}$$

[40] Respectively, $L_{kt} = \sum_{i=1}^{N_k} l_{ikt}$ and $X_{kt}^j = \sum_{i=1}^{N_k} x_{ikt}^j$ for each intermediate j.

Note that the condition can be also written as a cost-weighted average, see Edmond et al. (2018), and that is the functional form I use for the empirical estimation. To ease the comparison across different environments, equation (10) defines the sectoral markups in the second scenario as well.[41]

Finally, sectoral real profits D_{kt}, defined as $\sum_i d_{ikt}$, can be written as:

$$D_{kt} = \left(1 - \frac{1}{\mathcal{M}_{kt}}\right) \beta_k Y_t - \mathcal{F}^x_{kt}, \tag{11}$$

where $\mathcal{F}^x_{kt}$ represents the total overhead spending in sector k: $\sum_i \frac{\nu_{kt}}{\phi_{ikt}} \left[\left(\frac{1}{s_{ikt}}\right)^{\psi_{kt}} - 1\right]$.

Moving to the aggregate economy, finding an aggregate production function is a challenging task due to the presence of sector-specific marginal costs and input elasticities. A potential solution comes from the definition of the aggregate price in equation (9):

$$P_t = \prod_{k=1}^{N} \left(\mathcal{M}_{kt} \frac{\Xi_{kt}}{Z_{kt}}\right)^{\beta_k}.$$

By defining the aggregate marginal costs and the aggregate productivity as, respectively, $\Xi_t = \prod_{k=1}^{N} \Xi_{kt}^{\beta_k}$ and $Z_t = \prod_{k=1}^{N} Z_{kt}^{\beta_k}$, the aggregate markup is the one that satisfies:

$$\mathcal{M}_t = \prod_{k=1}^{N} \mathcal{M}_{kt}^{\beta_k}. \tag{12}$$

4 Shocks and Market Power

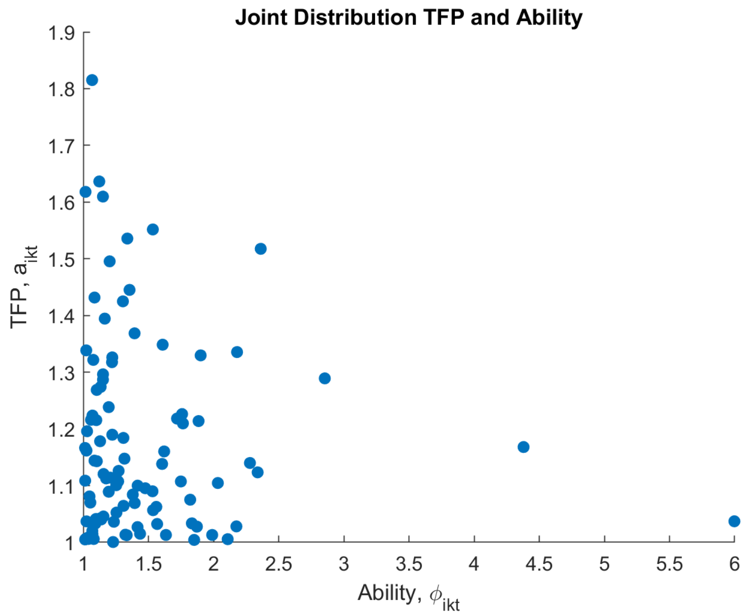
In this section, I study how *platform shocks* affect market power outcomes. These are defined as either shocks to the level, ν_{kt}, or to the curvature, ψ_{kt}, of the investment cost function f^x_{ikt}. Shocks are analyzed separately depending on their source, since the effects on the economy differ. The purpose of this study is to disentangle the key mechanism of the framework in a controlled scenario, before bringing the model to the data.

The economy is kept as simple as possible by modelling only two sectors: the first is where shocks happen, and it is used to isolate the direct impact of the shocks, while the second serves the purpose of highlighting the indirect propagation through the I-O structure.[42] Firms use a bundle of intermediates composed in equal shares by the sectoral

[41] It is harder to define the sectoral markup in scenario b as the sectoral productivity Z_{kt} misses information on investment. In other words, Ξ_{kt}/Z_{kt} is not a measure of sectoral marginal costs. The alternative is to define an effective productivity by augmenting Z_{kt} with s_{ikt}, although it is not the one coming from aggregation, and use it for the derivation of the sectoral markup. This gives the condition in the text.

[42] The environment is kept symmetric and homogeneous, which implies that β_k is 1/2 in both sectors, so that the observed dynamics are solely driven by sectoral shocks. Each sector is populated by $N_k = 100$ firms, while θ is equal to 5 and α_K to 0.56 in both sectors.

Figure 6: Joint distribution of implementation costs and productivity



Notes: The graph plots the realized distribution of TFP and implementation costs. This distribution is simulated once and kept constant across sectors. Firm-level productivity a_{ikt} is represented on the y-axis, while implementation costs ϕ_{ikt} on the x-axis, and each dot describes a firm.

production of the two sectors, and both implementation costs and productivity are drawn from continuous and independent Pareto distributions.[43] Appendix E reports the same experiment, but in a richer setting, to show that results are consistent in an environment characterized by more firms and sectors.[44]

In subsection 4.1, I present an environment where all firms are subscribed to the platforms, both before and after the shock takes place. In other words, the adjustments in investment occur on the intensive dimension. Results change if an inaction region exists, in which some firms decide to avoid subscribing. When this is the case, the shocks lead to adjustments both on the intensive and extensive margins, by altering the threshold for active investment behavior. This second environment is presented in subsection 4.2.

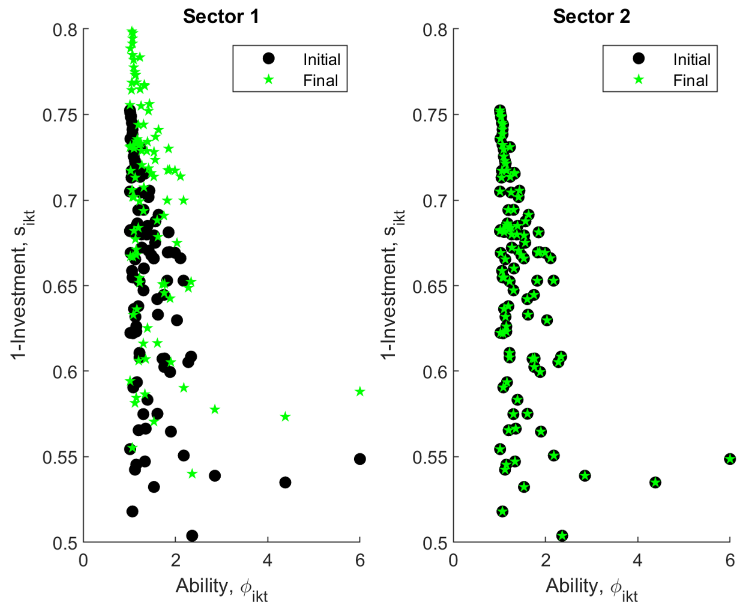
4.1 Intensive Margin Adjustments

Figure (6) represents the joint distribution of firm-level productivity a_{ikt} and implementation costs ϕ_{ikt}. Firms draw these two primitives upon birth from independent Pareto distributions. Firms' random draws are simulated once, and the realized distribution is

[43]Both distributions present a minimum $zmin = 1$, while the tail parameters are $\kappa_\phi = 3$ and $\kappa_a = 7$.

[44]Furthermore, I also replicate the simulations for the models presented in Appendix C, where the investment in the platforms lowers the intermediate costs only, either directly or indirectly.

Figure 7: Distribution of investment, pre and post shock to ν_{1t}



Notes: The graph plots the distribution of s_{ikt} in each sector. Since a higher investment results in a *lower* s_{ikt}, I refer to the latter as the inverse of investment. Initial scenario, black dots: sectors are homogeneous and symmetric. Final scenario, green stars: sector 1 only experiences a permanent increase in ν_{kt}. Each marker represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic implementation costs ϕ_{ikt}.

kept constant across the two sectors (and across the different simulations) to ease comparison.[45] Since the two draws are assumed to be independent, it can be seen how the majority of firms present relatively small TFP and implementation costs, while few are endowed with high a_{ikt} (y-axis) or ϕ_{ikt} (x-axis), and rarely both. To highlight the role of implementation costs, in this example the Pareto distribution for ability presents a ticker tail than the one for TFP, and this explains why firms are more extreme on the first dimension.

Figure (7) plots the distribution of investment in each sector, before and after a shock that permanently increases ν_{kt} in sector 1 only. Since a low s_{ikt} characterizes a larger investment, in the graphs I refer to the first as the inverse of investment. Note that, in this experiment, I impose a 100% increase to ν_{1t}; the same magnitude is kept for the shock to ψ_{1t} below, as well as in subsection 4.2.

In the pre-shock initial equilibrium, represented in black, sectors are completely homogeneous and symmetric: not surprisingly, the distribution of investment is the same across sectors. It is important to stress that, although the magnitude oscillates significantly between firms, each firm is investing a positive amount in the platforms. Overall,

[45]Given the large number of firms, simulations present minor differences if these draws are re-simulated.

the distribution presents a negative correlation between s_{ikt} and ϕ_{ikt}. This is trivial, since lower implementation costs lead to a larger investment *ceteris paribus*, i.e. to a lower s_{ikt}. However, investment is also affected by TFP: a firm endowed with a higher productivity invests more, as the benefit of the investment increases in the scale of production. This explains the observed differences in investment between firms endowed with the same implementation costs.

In the post-shock final equilibrium, depicted by the green stars, sector 1 only experiences the increase in ν_{1t}. The individual investment decision is clearly altered by the shock: the distribution moves up uniformly as ν_{1t} increases, meaning that each firm invests less resources when the investment costs are higher. These adjustments on the intensive margin represents the direct response to the shock. On the other hand, nothing happens to the optimal investment strategy in sector 2, since the distributions are exactly the same before and after the shock. These dynamics are invariant to the scenario studied: both under scenario *a* and *b*, the change in the investment behavior is the same, given that, as shown in Section 3, firm-level optimal decisions regarding investments and prices are the same in the two environments.

At the sectoral level, the variation in the investment strategy alters the average marginal cost: since each firm is investing less, the total abatement of costs is lower and, hence, marginal costs are higher. In turn, this increases firm-level prices and, thus, the sectoral price P_{1t}, while the total production of sector 1 shrinks. The I-O structure magnifies the transmission of the shock to sector 2, given that the sectoral good from sector 1 is an input of production in sector 2.[46] As a result, the sectoral price, marginal costs and production in sector 2 increase.[47]

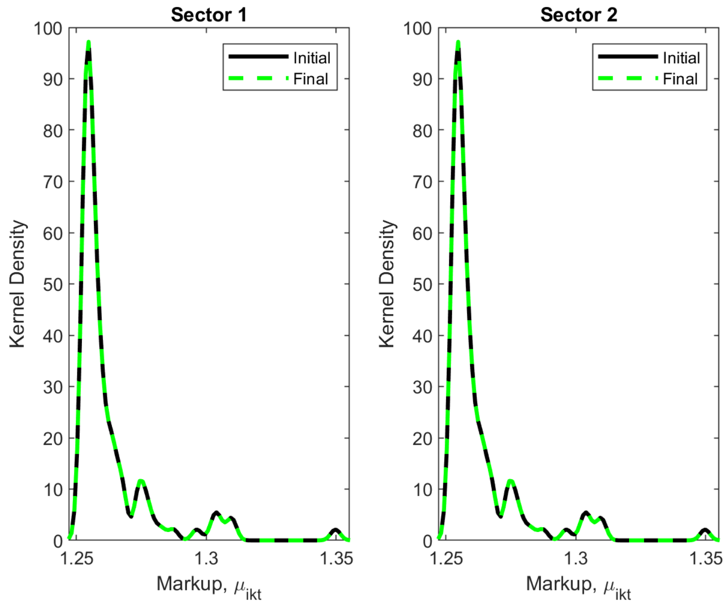
The dispersion in investment, driven by the variation in firm-level TFP and implementation costs, is responsible for the heterogeneity in firm-level markups and, ultimately, market power. Figure (8) plots the initial and final distributions of firm-level markups in the two sectors. Again, the two sectors share identical distributions before the shock takes place, since they are completely symmetrical. However, this is true also after the shock.

As it can be inferred from Figure (7), this happens because firms in sector 1 adjust their investment proportionally, in such a way that the relative size distribution is unaffected: the distribution of s_{ikt} moves up, without affecting the relative gaps between the firms. Since the distribution of market shares is unaltered, there is no change in market power outcomes. In other words, in this environment the sectoral markups and concentration are

[46]The propagation is discussed in details in Section 6.

[47]Note that the transmission of the sectoral shock is strong enough to affect the aggregate, as the aggregate price index P_t increases by more than 6%. Although, clearly, these results are affected by the number of sectors modelled, findings are qualitatively similar in Appendix E.

Figure 8: Distribution of markups, pre and post shock to ν_{1t}



Notes: The graph plots the kernel distribution of firm-level markups in each sector. Initial scenario, black lines: sectors are homogeneous and symmetric. Final scenario, green dashed lines: sector 1 only experiences a permanent increase in ν_{kt}.

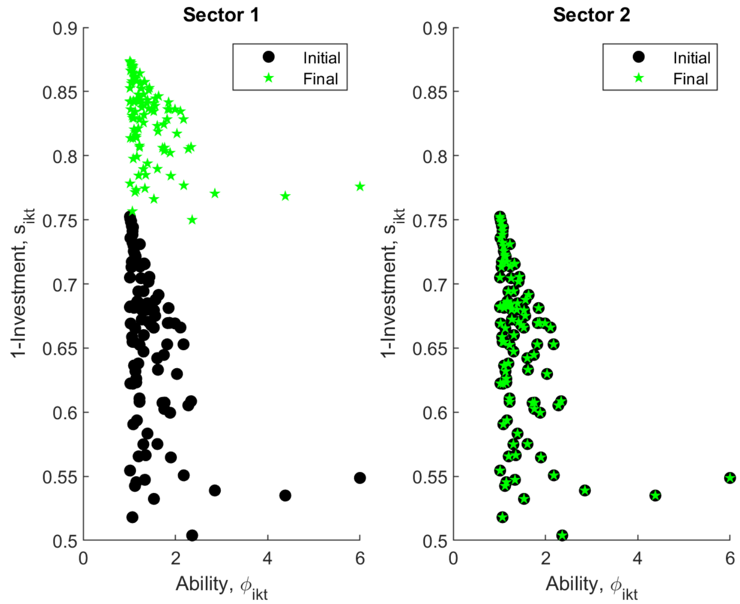
invariant to a shock to ν_{kt}. This finding shows how market power outcomes are altered only when shocks affect firm-level quantities disproportionally, as they are driven by relative, and not absolute, differences between firms.

All the results above are true for both scenarios. However, an important difference exists between the two environments, and it regards sectoral productivity. First, in the initial equilibrium the sectoral productivity is lower in scenario b than in scenario a, as in the first s_{ikt} does not result in efficiency gains, and, thus, it is not factored in the definition of Z_{kt}. Second, the sectoral productivity is invariant to the shock under scenario b: the distribution of a_{ikt} is given, and the relative output shares are not altered by this shock, consistently with the results in Figure (8).[48]

This is different in scenario a. Sectoral productivity goes down in response to the shock, in sector 1 only, due to the change in the investment behavior: an increase in ν_{1t} lowers welfare, as the economy is less productive given the contraction in the investment in the platforms. In other words, a proportional increase in the subscription fees for AWS lowers the intensity with which the platform is used, meaning that firms need to *waste* more time than before to perform unproductive activities, previously handled by the platform, hence

[48]Output shares are not moving when market shares are not, as the first can be written as $\frac{y_{ikt}}{Y_{kt}} = \left(\frac{p_{ikt}}{P_{kt}}\right)^{-\theta} = (q_{ikt})^{\frac{\theta}{\theta-1}}$

Figure 9: Distribution of investment, pre and post shock to ψ_{1t}



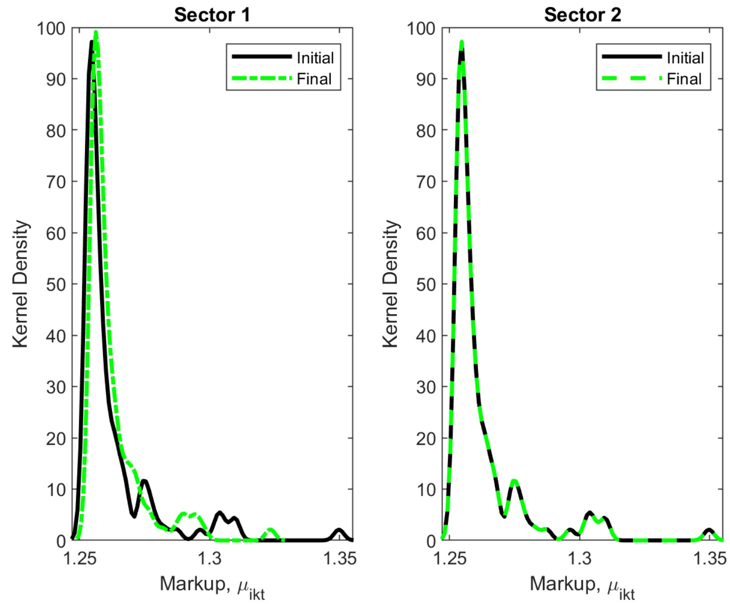
Notes: The graph plots the distribution of s_{ikt} in each sector. Since a higher investment results in a *lower* s_{ikt}, I refer to the latter as the inverse of investment. Initial scenario, black dots: sectors are homogeneous and symmetric. Final scenario, green stars: sector 1 only experiences a permanent increase in ψ_{kt}. Each marker represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic implementation costs ϕ_{ikt}.

losing in performance. This effect is lacking in scenario b, as firms invest to directly reduce costs, with no effects on efficiency.

To sum up, when all firms are investing in the platforms, shocks to the level of the investment costs do not alter market power dynamics: results differ considerably if the shock targets the curvature of the cost function, ψ_{kt}, as shown by Figure (9) and, in particular, by Figure (10). This happens because a shock to the curvature parameter brings non-linear effects by constructions, as it alters both the mean and the variance of the investment distribution: the relative impact of the shock is stronger for high-investment firms, as their exposure is higher.

Figure (9) shows that not only the distribution moves upward, as for the shock to ν_{1t} described in Figure (7), but the dispersion of the investment shrinks considerably: in response to shock, each firm reduces its own investment in sector 1, but the more they were investing, the more they cut. This non-linearity has a key implication for the propagation of the shock, from the investment to market power outcomes: the change in the relative investment affects the distribution of market shares, differently from the previous experiment. These non-linear firm-level adjustments drive the observed response in markups, which can be seen in Figure (10).

Figure 10: Distribution of markups, pre and post shock to ψ_{1t}



Notes: The graph plots the kernel distribution of firm-level markups in each sector. Initial scenario, black lines: sectors are homogeneous and symmetric. Final scenario, green dashed lines: sector 1 only experiences a permanent increase in ψ_{kt}.

Figure (10) shows how the dispersion of firm-level markups in sector 1 shrinks in response to the shock, as high-markup firms are hit the hardest. This result can also be seen analytically: the ratio of the markups between two randomly chosen firms in a given sector k can be written as:

$$\frac{\mu_{1kt}}{\mu_{2kt}} = \frac{a_{1kt}}{a_{2kt}} \left(\frac{\phi_{1kt}}{\phi_{2kt}}\right)^{\frac{1}{\psi_{kt}}} \frac{f(q_{1kt})}{f(q_{2kt})}.$$

Thus, considering for simplicity only the immediate effect of the shock, the ratio is invariant to a shock to ν_{kt} but not to ψ_{kt}: assuming that firm 1 is endowed with lower implementation costs ϕ_{ikt}, the ratio shrinks as ψ_{kt} increases, meaning that the competitive advantage firm 1 has is eroded by an increase in the curvature parameter. The reduction in the dispersion of market shares and markups results in a decrease in sectoral markup and concentration in sector 1.

As for the shock to ν_{kt}, the results discussed above are the same across both scenarios except for sectoral productivity. Z_{kt} decreases in scenario a due to the strong contraction in investment, which affects overall efficiency. However, it weakly increases in scenario b, approximately by a tenth in magnitude with respect to the decrease in scenario a under the current parametrization. This increase occurs as the distribution of output shares is altered due to the non-linear adjustments in investment. The fact that sectoral productivity increases suggests reallocation toward highly productive firms. This happens as the dispersion of markups is a measure of allocative efficiency: when the first shrinks, misallocation of resources is reduced, consistently with the discussion in Edmond et al. (2018). The distributional changes can be seen in the distribution of profits, which resemble the one for markup and is presented in Appendix F, and result in an increase in sectoral profits.

To sum up, whenever all firms are actively investing through the platform, any shock to the level of the investment cost ν_{kt} trigger strong adjustments in prices and quantities that propagate to the rest of the economy. However, the shock is absorbed in its entirety by the price, and market power indexes are unaffected. This changes if the shock hits the curvature parameter ψ_{kt}, as the shock alters the distribution of markups and market shares. This results in a decline in sectoral concentration and markups, but at the cost of lower sectoral productivity (under scenario a only). In other words, this experiment proxies an event in which platforms increase their prices while also lowering the number of services they offer, effectively reducing the dispersion in investment.[49]

4.2 Intensive and Extensive Margins Adjustments

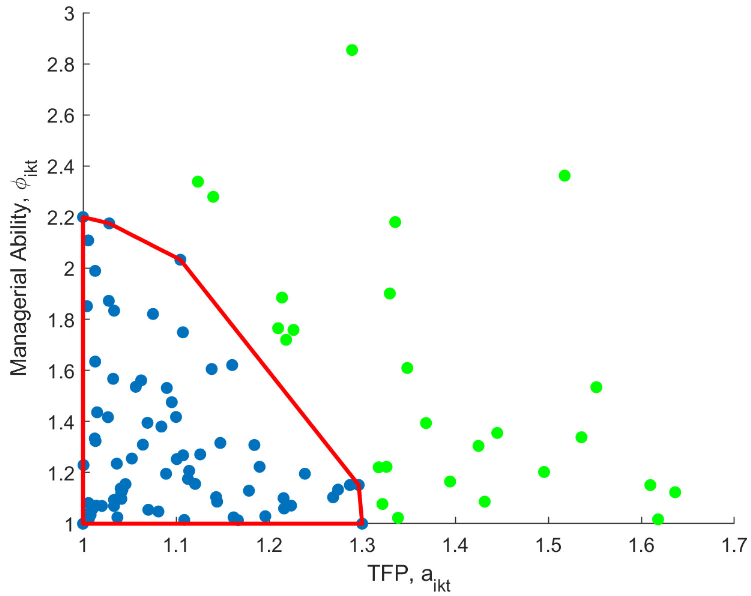
This subsection reproduces the previous simulations, but in a slightly different environment: as for the experiments above, the economy starts in an equilibrium where the two sectors are identical. However, the initial value of ν_{kt} is increased in both sectors with respect to the previous case.[50] The change is such that an inaction region emerges: below a certain threshold, function of ϕ_{ikt} and a_{ikt}, firms optimally decide to invest no resources in the platforms, i.e. $s_{ikt} = 1$. If this is the case, their performances are solely driven by their idiosyncratic productivity a_{ikt}. To ease comparison, note that the underlying distribution of TFP and implementation costs is the one from the previous subsection.

Figure (11) plots the inaction region as a function of TFP and implementation costs. Firm-level productivity a_{ikt} is represented on the y-axis, while implementation costs ϕ_{ikt} on the x-axis, and each dot describes a firm. Blue dots describe firms inside the inaction region, i.e. their optimal investment is zero, or $s_{ikt} = 1$, the frontier is represented in red, while green dots represent firms with positive investment in the platforms. It is clear from the graph how the two primitives reinforce each other: either firms are investing because endowed with a high productivity or implementation costs, or because their combination is above the threshold.

[49] All the results of the subsection are qualitatively the same if the model is the one from Appendix C, i.e. when the investment enters production non-linearly or it scales down only the intermediate costs.

[50] Specifically, it increases from $5e^{-4}$ to $5e^{-2}$. Note that here the key is not to quantify the increase, but to create an inaction region.

Figure 11: Inaction region



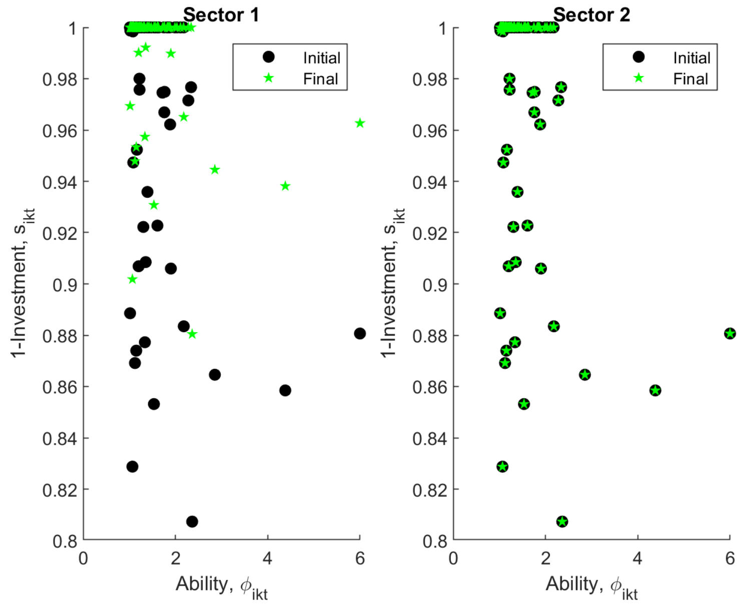
Notes: The graph plots the inaction region as a function of TFP and implementation costs. The underlying distribution is the one from Figure 6, censored at the top for readability. Firm-level productivity a_{ikt} is represented on the y-axis, while implementation costs ϕ_{ikt} on the x-axis, and each dot describes a firm. Blue dots describe firms inside the inaction region, i.e. their optimal investment is zero, or $s_{ikt} = 1$, the frontier is represented in red, while green dots represent firms with positive investment in the platforms.

Figure (12) plots the distribution of investment in the two sectors. Due to the higher baseline value of ν_{kt}, the initial distributions move upward with respect to the ones in subsection 4.1. However, while doing so they hit a ceiling: as firms cannot disinvest, the optimal investment cannot go below zero, i.e. above $s_{ikt} = 1$: firms *stuck* in the area where investment is zero belong to the inaction region. In this environment, and differently from the simulation in Figure (7), the shock to ν_{kt} does not affect each firm with the same magnitude: due to the existence of the inaction region, an increase in the investment costs has no direct effect on the firms that were already choosing not to invest in the platforms.[51]

Moreover, the shock to ν_{kt} triggers two types of adjustment: on the intensive margin, investing firms react by down-scaling their investment, with the same effects on prices and quantities described in subsection 4.1. Graphically, the distribution moves upward, representing an uniform decline in investment among active firms. On the extensive margin, some firms optimally choose to leave the platforms due to the increase in costs. This can be inferred from Figure (12): the fact that the inverse of the investment has an upper

[51]The shocks to ν_{kt} and ψ_{kt} in this subsection are the same, in percentage, as in subsection 4.1, although the levels are different.

Figure 12: Distribution of investment, pre and post shock to ν_{1t}



Notes: The graph plots the distribution of s_{ikt} in each sector. Since a higher investment results in a *lower* s_{ikt}, I refer to the latter as the inverse of investment. Initial scenario, black dots: sectors are homogeneous and symmetric. Final scenario, green stars: sector 1 only experiences a permanent increase in ν_{kt}. Each marker represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic implementation costs ϕ_{ikt}.

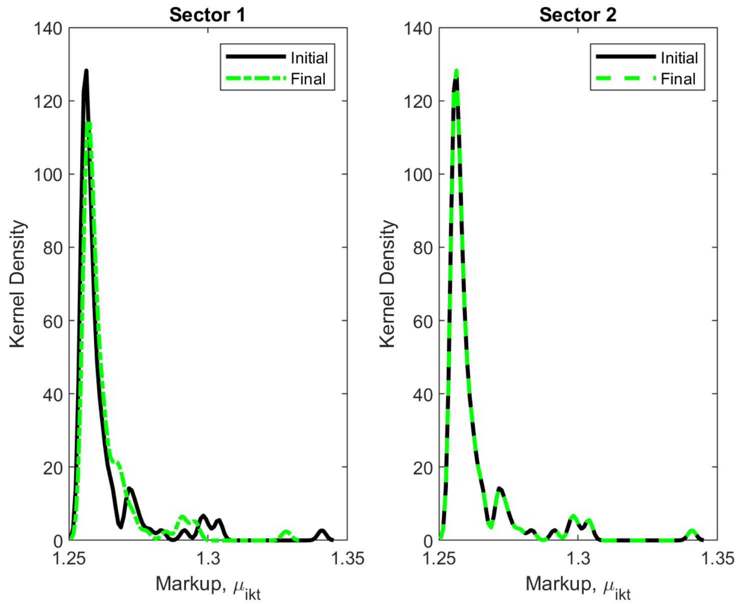
bound in 1 results in the distribution hitting a plateau when shifting upward. This means that firms in the proximity of the inaction region are not free to fully adjust, or, in other words, that the inaction region from Figure (11) moves outward.

The asymmetry around the inaction region is the reason why a uniform increase in ν_{1t} shrinks investment dispersion when an inaction region exists. This represent the key difference with respect to the case in subsection 4.1: due to the fact the the dispersion of investment is altered, a shock to ν_{kt} now carries non-negligible effects on market power outcomes. Figure (13) shows the distribution of markups. Clearly, the distribution in sector 1 is affected, as it presents a shift to the left, which reduces dispersion.

At the sectoral level, market power outcomes move in response to the shock: the change in the distribution of market shares and markups results in a lower sectoral markup and concentration in sector 1, as high-investing firms are hit the hardest by the increase in the investment costs. Again, the effects on sectoral productivity depend on the scenario modelled: under scenario *a* productivity decreases due to the drop in investment, while under scenario *b* it increases due to reallocation, originating from the increase in the relative competitiveness of medium firms.

Finally, Figure (14) presents the simulation where sector 1 experiences a sudden in-

Figure 13: Distribution of markups, pre and post shock to ν_{1t}

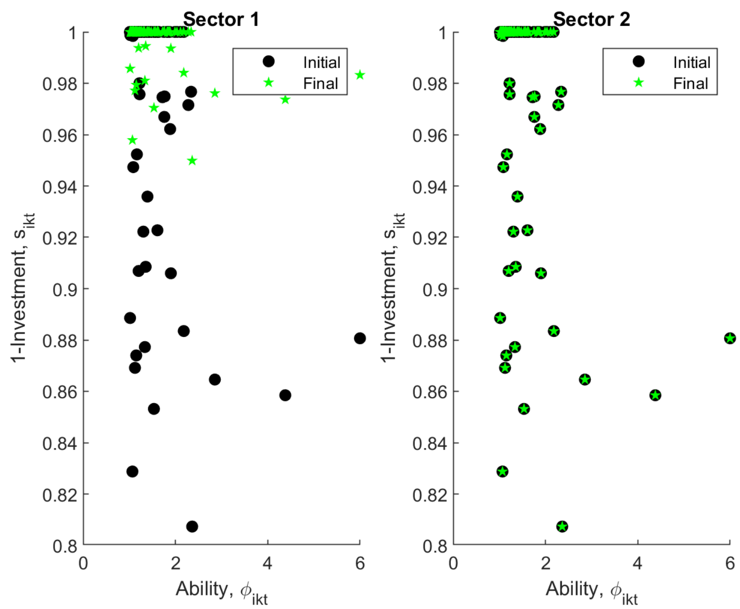


Notes: The graph plots the kernel distribution of firm-level markups in each sector. Initial scenario, black lines: sectors are homogeneous and symmetric. Final scenario, green dashed lines: sector 1 only experiences a permanent increase in ν_{kt}.

crease in ψ_{kt}, and an inaction region exists. This time, results are quite similar to the case discussed in subsection 4.1: the key implication of the inaction region is to introduce asymmetry in the size of (relative) adjustments in investment between firms away from, close to and inside the inaction region, as their exposure to the shock differ. However, a shock to the curvature ψ_{kt} already brings non-linear adjustments by design. In other words, the presence or lack of an inaction region might change quantitatively the results, although differences are minor under these experiments, but the qualitative implications of a shock to ψ_{kt} are the same.

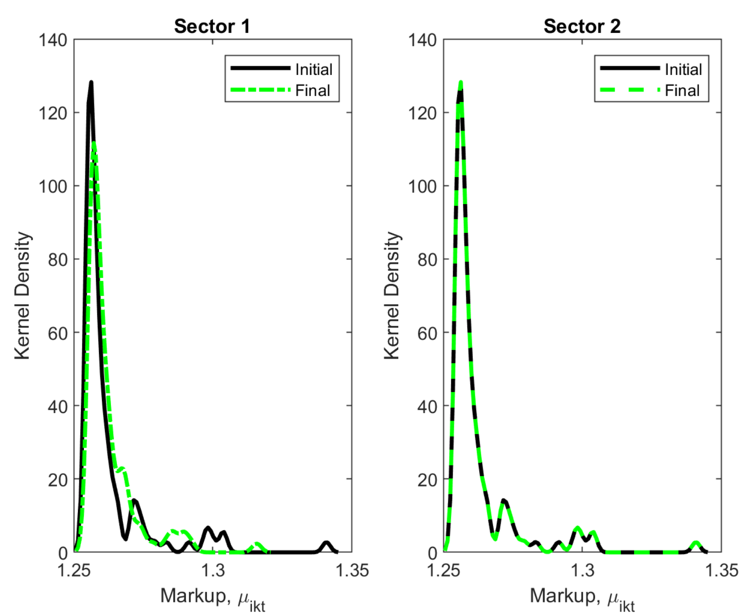
Indeed, (14) confirms that results are similar to the ones in subsection 4.1. After the shock, the distribution of s_{ikt} moves upward in sector 1. The presence of adjustments even on the extensive margin does not alter the impact of the shock on market power outcomes: although the shock carries no effects for inactive firms, and the effect is mitigated for firms close to the threshold, the sectoral effects are driven by the top firms. Firms that invest large amounts with the platforms, or that, more in general, display large market shares, matter disproportionally more for sectoral market power outcome. As their adjustments are not affected to a first order by the presence or the lack of an inaction region, since firms in that region are not direct competitors of the market leaders, the effects of the shock to ψ_{kt} is similar.

Figure 14: Distribution of investment, shock to ψ_{1t}



Notes: The graph plots the distribution of s_{ikt} in each sector. Since a higher investment results in a *lower* s_{ikt}, I refer to the latter as the inverse of investment. Initial scenario, black dots: sectors are homogeneous and symmetric. Final scenario, green stars: sector 1 only experiences a permanent increase in ψ_{kt}. Each marker represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic implementation costs ϕ_{ikt}.

Figure 15: Distribution of markups, shock to ψ_{1t}



Notes: The graph plots the kernel distribution of firm-level markups in each sector. Initial scenario, black lines: sectors are homogeneous and symmetric. Final scenario, green dashed lines: sector 1 only experiences a permanent increase in ψ_{kt}.

This is confirmed by the results in Figure (15). The dispersion of markups in sector 1 shrinks in response to the shock. The change in the distribution of markups and market share implies that the sectoral markup and concentration are lower in sector 1 in response to shock. To conclude, results are consistent under both scenarios, and, again, the only difference lies in the response of sectoral productivity.

5 Aggregate *Amazon Shock*

The following experiment quantifies the impact of e-commerce platforms, Amazon in particular, on market power outcomes in the US. As discussed in Section 4, changes to the investment behavior in response to shocks can alter market power measures, depending on the presence of an inaction region or due to the nature of the shock itself. The goal of this section is to disentangle this mechanism from other underlying phenomena that might have altered markups, concentration, and productivity over the same time frame.

I first calibrate an initial *pre-platform* scenario that serves as the initial equilibrium for the study. This equilibrium is calibrated to match targets from the US economy in 1997, right after Amazon started to operate in July 1995 as an online bookstore, but way before *B2B* services as AWS or Amazon Business were active. Since the environment describes a scenario without e-commerce platforms, investment is constrained to zero. Then, I contrast this equilibrium to a final scenario, which is calibrated to the US economy in 2016. As this environment represents an environment characterized by a massive presence of e-commerce platforms, firms are now free to invest.

To disentangle the impact of this *Amazon shock*, I build a counterfactual economy that shares the same calibration with the *true* 2016 economy with platforms, but constraining investment to be nil. Although this environment does not allow investment in the platforms, it still captures through its calibration several underlying trends that characterized the US economy in the last three decades. Just to mention a few, it accounts for the dynamics in sectoral market power, labor share, number of firms, distribution of productivity, while allowing sectors' sizes and I-O linkages to adjust over time as well.

Thanks to this counterfactual, it is possible to isolate the role of platforms: I can first contrast the 1997 economy to the 2016 one with investment and quantify the change in market power and productivity. Then, I can do the same but using the counterfactual 2016 economy without platforms, and check how much these trends are affected. This explains the impact of the investment in the platforms, since it is the only dimension in which the true and the counterfactual 2016 scenarios differ.

5.1 Calibration

The calibration follows. In every equilibrium, the aggregate wage of the economy, W, is normalized to 1, while the GDP of the economy, Y, is set to 15000. The latter is exogenous in a partial equilibrium model as this one. Finally, N is calibrated to 15. This means that the economy presents 15 sectors, which are calibrated to the NAICS-2 sectors presented in Section 2. The remaining parameters of the economy are calibrated for each sector, allowing the targets to change between 1997 and 2016. To simplify the notation, in the following I drop the subscript $_t$ from the parameter, but note that each parameter is calibrated for each sector twice, once for each time frame.

The targets are the following: the number of firms in each sector, N_k, is calibrated to the empirical counterpart from Compustat in 1997 and 2016.[52] Using data from the Bureau of Economic Analysis (BEA), I use sectoral production to calibrate β_k such that the relative size of each sector is consistent with the data. Given N_k, I use the calibration of θ_k to target the sectoral markups from 1997 and 2016. A perfect match with the targets is challenging here: the sectoral markup is an endogenous, and stochastic, object under oligopolistic competition, function of the other parameters and the realized joint distribution of productivity and implementation costs. To proxy for it, I define a simplified sectoral markup $\mathcal{M}_k$ under firms homogeneity, which is equal to $\frac{\theta_k}{\theta_k-1}\frac{N_k}{N_k-1}$. Given the empirical markups, I can invert this equation to solve for the elasticity between goods θ_k. Figure (16) presents sectoral markups and concentration, showing the goodness of the fit.

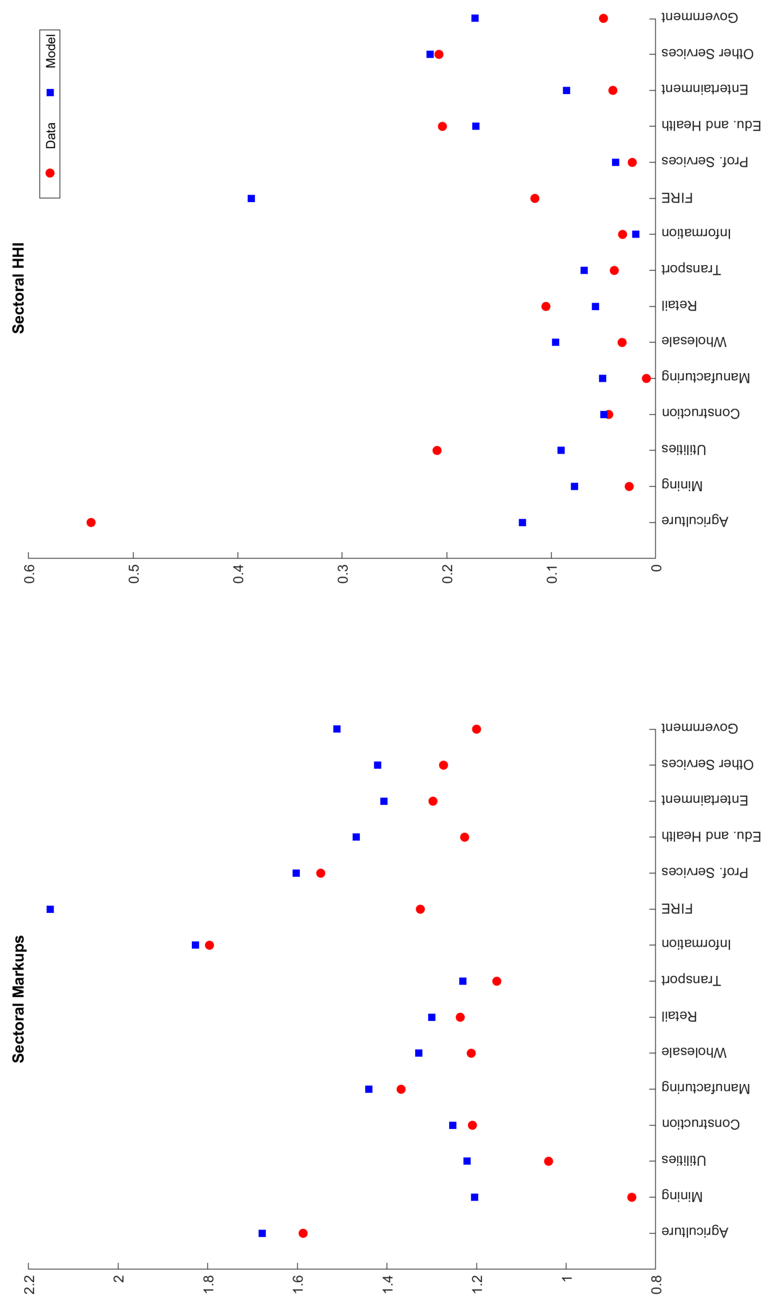
The Bureau of Labor Statics (BLS) provides data on the sectoral labor share: this is the target for the calibration of α_K in the different environments. The elasticities ω_{Kj} are calibrated using the Use Input-Output tables from the BEA. In this way, the I-O linkages reflect the underlying structure of the US production in 1997 and 2016. Finally, each sector presents a different underlying distribution from which firms draw their TFP. The distribution is a continuous Pareto function with a minimum in 1 and a tail parameter κ_k. The sector-specific tail parameter is calibrated to target the sectoral Herfindal index. Colciago and Silvestrini (2022) show that, in a similar framework populated by a continuum of heterogeneous firms and overhead costs in production, the Herfindal index can be written as, adjusting for sectoral dynamics:

$$HHI_k = \frac{\theta_k\left[\kappa_k - (\theta_k - 1)\right]}{\kappa_k - 2\left(\theta_k - 1\right)}\frac{f_k^x}{Y_k},$$

where f_k^x/Y_k is the sectoral overhead expenditure as a share of production. Given the

[52] Business Dynamics Statistics (BDS) might deliver better estimates, as they cover the entire universe of firms. On the other hand, Compustat is used here for consistency, as the market power measures are based on Compustat as well, and for computational issues. Still, this calibration delivers a sufficiently large number of firms, with thousands observations.

Figure 16: Sectoral markups and concentration, 2016 model and data



Notes: The graph presents the sectoral markup, first panel, and sectoral concentration, second panel, from 2016. Red dots represent the estimates from the data, blue squares the simulated counterparts.

estimated θ_k and using data on sectoral concentration and the overhead share, I pin down the tail parameter κ_k. The calibration and its targets are summarized in Table (2) below.[53]

Table 2: **Calibration, targets for 1997 and 2016**

Parameter	Description	Target
N_k	Sectoral number of firms	Number of firms per sector, Compustat
β_k	Sectoral market share	Sectoral production shares, BEA
θ_k	Elasticity of sub. between goods	Sectoral markups, Compustat
α_K	Elasticity labor in production	Sectoral labor share, BLS
ω_{Kj}	Elasticity intermediate j	I-O linkages, Use Tables BEA
κ_K	Tail parameter Pareto TFP	Sectoral Herfindal Index, Compustat

Notes: The table presents the calibration of the exogenous parameters. Each parameter is calibrated in each sector twice, once using the target from 1997 US data, once from 2016. Parameters calibrated for 2016 are kept constant under the scenarios with or without investment in the platforms.

For the *true* 2016 economy, i.e. the one characterized by the investment in the platforms, it is key to first discipline how much firms are investing: quantitative assessments can be performed only when the average investment and its dispersion are consistent with the data. To do so, the calibration of the investment costs parameters ψ and ν is crucial.[54] As targets, I use data on AWS usage, presented in Section 2: ψ and ν are calibrated such that (i) the economy presents an action region of approximately $10 - 15\%$ and that (ii) the ratio between the investment of the top 1% firms and the lower 50 percent is 1000.[55]

Note that this is a conservative estimation, since it is based on the usage of AWS only, abstracting from other Amazon services like Business Prime or other providers as Alibaba or Google Cloud Services. This is why the aforementioned targets are considered as lower bounds. On the other hand, the fact that the initial equilibrium from 1997 presents no investment at all might exaggerate the impact of the platforms, given that different but comparable intermediaries and services already existed.

However, the digital revolution completely changed the way in which intermediation works, both in terms of reach, given the huge numbers of buyers and sellers from multiple sectors active on e-commerce platforms, and regarding costs and accessibility. The same can be said for the innovation in cloud computing, analytics, and machine learning: this breakthrough justifies the choice of a *new* margin to be exploited by the firms.[56] To close the calibration, the underlying distribution from which firms draw their implementation costs is a continuous Pareto distribution with tail parameter equal to 3. The calibration

[53]For the values chosen in each sector, see the replication package.

[54]For simplicity, here I calibrate ψ and ν once for the whole economy in 2016. The study in which these parameters are subject to sector-specific shocks is presented in Section 7.

[55]A perfect calibration is numerically impossible: the parameters are guessed until the equilibrium converges to the targets.

[56]More conservative scenarios with limited shocks to the investment costs are presented in Section 6.

of the investment costs is summarized in Table (3) below.

Table 3: **Calibration investment costs, targets for 2016**

Parameter	Target
ψ	Ratio investment top 1% to bottom 50% $\approx$ 1000
ν	Investment action share $\approx$ 15%

Notes: The table presents the calibration of the exogenous parameters for the investment costs in the 2016 economy.

5.2 Results

The results from the simulations are shown in Table (4).[57] To show the robustness of the results, the 1997 is contrasted to the 2016 economy with no investment, to the 2016 economy with investment and presenting both scenario a and b, and, also, to a 2016 economy with investment from the model presented in Appendix C. In the latter, I study two scenarios: scenario *a'*, which resemble scenario a in the baseline, where the benefit of the investment affect production, but non-linearly as a intermediate augmenting technology, and scenario *b'*, analogous to b, where the investment affect the variable costs, but only affecting intermediates costs and not the wage bill.

Table 4: **Results Model Simulation**

	1997	% change 2016		% change 2016, App. C		% change 2016, counter.
$\mathcal{M}$	1.39	12.55%		10.17%		7.12%
HHI	0.059	67.08%		32.48%		5.44%
		ver. a	b	version *a'*	*b'*	
Z	11.40	63.50%	23.86%	40.54%	24.38%	22.95%

Notes: The table presents the results of the simulation. The first row reports the aggregate markup in level for 1997 and its percentage change between 1997 and 2016 in, respectively, the *true* model, the alternative version with the model from Appendix C, and the counterfactual model with no investment in the platforms. The same goes for the second and third rows for concentration and aggregate productivity. Regarding productivity, when investment is non-zero I distinguish between scenario a and *a'*, where investment affects production, and scenarios b and *b'*, where investment directly lowers costs.

Moving from 1997 to 2016, markups, concentration and productivity increase in all frameworks. However, the magnitude of the increase differs depending whether the investment in the platform is allowed. The increase in the aggregate markup equals approximately 13 percent in the baseline, consistently with the empirical evidence uncovered in Section 2, while it is weaker when investment is not allowed. Comparing the two models, the investment in the platforms can explain 43.27% of the simulated trend in markup,

[57]Note that the joint distribution of TFP and implementation costs from 2016 is simulated in each sector once, and then they are kept the same across the different scenarios and counterfactual for 2016.

while the remaining share is due to other phenomena, captured by the change in the targets of the calibration. This difference also exists for the model from Appendix C, although in this case the part that is lost when investment is constrained is lower: in other words, investment here can explain 29.94 percent of the generated pattern.

A similar picture can be painted for market concentration: the Herfindal index increases by 67% in the baseline model, which is close to the empirical growth of 52% from Compustat data, and it increases in the other specifications as well. However, this time the vast majority of the increase can be attributed to the investment behavior. In numbers, 92% of the change is explained by the investment in the platforms, given that in the counterfactual experiment the HHI increases by only 5 percent, while the percentage is 83 in the model from Appendix C.

Regarding productivity, I distinguish between the two scenarios when investment is allowed to occur: scenario *a* and *a'*, where investment affects production, and scenarios *b* and *b'*, where investment directly lowers variable costs. For the first, results differ across models since the productive investment in the platforms is factored in the definition of productivity: the aggregate productivity already increases by 14% in the counterfactual model, due to the underlying changes in the distribution of TFP. On top of these, the presence of investment further pushes productivity up, and this is why productivity grows by 19 percent in the baseline model. The alternative model is in between the two experiments: investment is productive and fosters productivity growth, but the fact that it scales down with the sector-specific intermediate share lowers its benefits, without affecting the costs. As a result, the intensity of the investment in the platforms is lower than in the baseline, hence the smaller increase in aggregate productivity. Under scenario *b* and *b'*, differences are milder: productivity simply depends on the distribution of firm-level TFP a_{ikt}, which is the same across all the 2016 models, and on the relative output shares, similar between the simulations.[58]

To sum up, the rise of the platforms, and of the investment in these intermediaries, exacerbated the increase in markups and concentration, and it can explain a non-negligible fraction of the observed increase in market power. On the other hand, this trend brought benefits: focusing on scenario *a* and *a'*, the investment in the platforms is productive, as it improves firms' efficiency, and, ultimately, it can increase aggregate productivity. Thus, there is a trade-off: top firms in selected sectors invest a huge amount of resources in the platforms, both in the model and the data, to increase their market power even more. As shown, this explains part of the increase in markups and concentration. The pattern entails welfare costs, as the increase in markups and in its dispersion act as taxes

[58] The fact that productivity increases between 2016 and 1997 is driven by the change in the Pareto tail parameters (and in sectors' sizes), consistently with Olmstead-Rumsey (2019).

on the economy, see Edmond et al. (2018). On the other hands, investments in platforms as AWS, Oracle but even Amazon Business Prime make firms better, since they improve their logistic, warehousing and, in general, efficiency, and this is reflected in welfare gains, as shown by the increase in aggregate productivity.[59]

Finally, it is useful to show how results change if we restrict firms to compete under monopolistic competition instead of oligopolistic competition. By neglecting this dimension, the findings might be misleading, as shown by Table (5). Given that firms are stuck to a markup of $\theta_k/(\theta_k - 1)$ no matter their size, which is the lower bound of the markups under oligopolistic competition, the aggregate markup, and its variation with respect to 1997, is clearly lower.

On the other hand, the increase in concentration is stronger than in the baseline framework: as shown by Edmond et al. (2018), large high-markup firms are sub-optimally small, due to the imperfect pass-through caused by the presence of endogenous markups. By removing markup dispersion, hence by moving to a monopolistic competition environment, high-markup firms are getting even larger. Since these firms are more productivity and/or endowed with lower implementation costs, this entails a reduction in the misallocation of resources, as production processes are relocated toward better firms. This explain why concentration increases in this counterfactual, but also why aggregate productivity does the same.

Table 5: **Model simulations, oligopolistic vs. monopolistic competition**

	2016, olig.		2016, mono.		2016, App. C, olig.		2016, App. C, mono.	
$\mathcal{M}$	1.56		1.32		1.53		1.32	
HHI	0.099		0.199		0.078		0.144	
	ver. *a*	*b*	ver. *a*	*b*	version *a'*	*b'*	version *a'*	*b'*
Z	18.64	14.12	19.28	14.55	16.02	14.18	16.76	14.82

Notes: The table presents the results of the simulation and the counterfactuals with monopolistic competition. The first row reports the aggregate markup in level for 2016 in, respectively, the baseline model, the counterfactual with monopolistic competition, the alternative model from Appendix C, and the counterfactual model from Appendix C, with monopolistic competition. The same goes for the second and third rows for concentration and aggregate productivity. Regarding productivity, when investment is non-zero I distinguish between scenario *a* and *a'*, where investment affects production, and scenarios *b* and *b'*, where investment directly lowers costs.

These results show the importance of oligopolistic competition, and why it should be taken into account when evaluating welfare: the welfare costs and benefits are strongly altered under monopolistic competition. The welfare costs associated with the rise of

[59]Given the effects on markups, profits and welfare, one might ask about entry and exit patterns, as they could balance the observed trends. In this setting, I abstract from this dimension, although the number of firms is free to adjust between steady states. In general, it should be noted that entrants are often small and they need time to invest, see Carvalho and Grassi (2019), and, thus, their impact is likely to be minor.

markups are reduced, since the lower aggregate markup, while the benefits are increased, given the higher aggregate productivity due to the decline in misallocation. In other words, assessing the impact of the rise of the investment in e-commerce platforms under this counterfactual would underestimate the welfare costs it implied.

6 I-O Propagation

The following simulations present a different approach: while in Section 5 all parameters are free to adjust across sectors and time, here parameters are calibrated once, either at the aggregate or sectoral level, and kept constant across the different experiments. The only parameters that are allowed to change over time are the ones that determine the investment costs, ν_{kt} and ψ_{kt}. In other words, I allow investment costs shocks to occur, and this is the scope of this study.

The purpose of the experiment is to show how shocks to the curvature parameter ψ_{kt} affect market power outcomes, depending on the sectors in which they happen. This is the main difference with respect to the previous simulation, in which ν_{kt} and ψ_{kt} are calibrated once and at the aggregate level. Conversely, in the following sections I model sectoral shocks to the curvature ψ_{kt}, thus allowing this parameter to change over time.

In Section 6, I focus on the propagation of the same exact shock, a 20% reduction of ψ in a given sector k, to study how the transmission differ depending on the sector in which the shock occurs, thus highlighting the magnification from the I-O structure.[60] In Section 7, I quantify and calibrate the sectoral shocks, allowing them to be sector-specific. The goal is to and exploit these shocks, and their sectoral variation, to explain the observed heterogeneity in sectoral market power trends.

6.1 Calibration

The calibration for the experiment follows. The core parameter of interest, ψ_{kt}, is allowed to change over time in response to shocks. As a baseline, the initial level is $\psi_{kt} = 10$ in all sectors, while the other parameter that disciplines the investment in the platforms, ν_{kt}, is set to 0.01. If the shock occurs to sector k, ψ_{kt} is always decreased by 20%. The remaining parameters of the model are kept constant across experiments, and they are described below.

Since individual, sectoral and aggregate prices are kept in level, wages W_t are normalized to one without loss of generality. As the model is in partial equilibrium, the total

[60]The section reports simulations for the baseline model, abstracting from the alternative model presented in Appendix C. The reason is that, in the latter, switching off the I-O linkages to asses the extent of propagation mechanically drives investment to zero.

size of the economy Y_t is exogenous. I fix the total GDP to a value of 1500. The economy presents 15 sectors, the same as in Section 5, and they represent the NAICS-2 sectors reported in the Bureau of Economic Analysis (BEA) tables.

In the following, the targets of the calibration take 2010 as the baseline year. Using BEA data, it is possible to calibrate the β_k such that they represent the relative size of each sector to the US GDP. This delivers shares ranging from approximately 1.5 percent in Agriculture, Mining or Utilities to 20% in Manufacturing and FIRE (Finance, Insurance, Real Estate and Rental). Note that this calibration delivers a constant in aggregation $\gamma_Y = 11.10$.

Regarding the I-O structure of the economy, the elasticities of the intermediates in the production function, ω_{Kj}, are calibrated following the Use I-O table of the BEA. Each value is then re-scaled by $(1 - \alpha_K)$, where α_K is the sectoral labor share, such that constant return to scale holds. The replication package reports the estimated elasticities for each sector. In general, the matrix presents a lot of mass on the diagonal elements, but is not sparse, and sectors show important heterogeneity, with cross-elasticities going from 0 to almost 35 percent, e.g. Construction from Manufacturing.

The remaining parameters are calibrated once and kept homogeneous across sectors. The goal is to capture sectoral heterogeneity only in sectors' sizes and I-O linkages to disentangle the extent of the propagation through the I-O structure, which is the focus of this section. The other dimensions are controlled for by calibrating the parameters to realistic values, but common across sectors. The parameters that govern the sectoral labor share, α_K, are fixed to a value of 0.56 in each sector, a calibration that reflects the median labor share from BEA, see Grassi (2017). Each sector is populated by $N_k = 578$ firms, which is the median number of firms from the BEA I-O tables for NAICS-4 sectors, see Grassi (2017).[61]

Regarding the goods market, the elasticity of substitution between goods, θ, is equal to 5, well within range with respect to the estimates in Bernard, Eaton, Jensen, and Kortum (2003). Note that this parameter pins down the lower bound for the idiosyncratic markup, equivalent to the monopolistic competition markup, to a value of 1.25. Finally, both firm-level implementation costs and productivity are described by a random draw from known continuous and independent Pareto distributions. Both these distributions present a minimum $zmin = 1$, while the tail parameters are, respectively, $\kappa_\phi = 3$ and $\kappa_a = 7$.[62]

[61] This number is significantly lower than the median for NAICS-2 sectors. However, it comes with computational advantage: as it is always possible to scale up or down the scale of the economy accordingly, keeping a smaller number of firms improves the speed of the algorithm with minor losses in terms of fit with the quantities of interest.

[62] For the purpose of this study, the tail parameters affect the results only qualitatively.

Table 6: **Calibration of the exogenous parameters**

Parameter	Value	Target
W_t	1	Normalization
Y_t	1500	Exogenous
N	15	Number of NAICS-2 sectors, BEA
N_k	578	Median number of firms BEA, Grassi (2017)
β_k	[0.014 : 0.19]	Relative share sectors, BEA
θ	5	$\mu^{MC} = 1.25$, Bernard et al. (2003)
α_K	0.56	Median labor share BEA, Grassi (2017)
ω_{Kj}	[0 : 0.33]	Use Table I-O structure, BEA
$zmin$	1	Normalization
κ_ϕ	3	Granular heavy-tailed distribution
κ_a	7	Granular medium-tailed distribution

Notes: The table presents the calibration of the exogenous parameters for the experiment. All sectors share the same values for the parameters shown, except for β_k and ω_{Kj}, which are sector-specific.

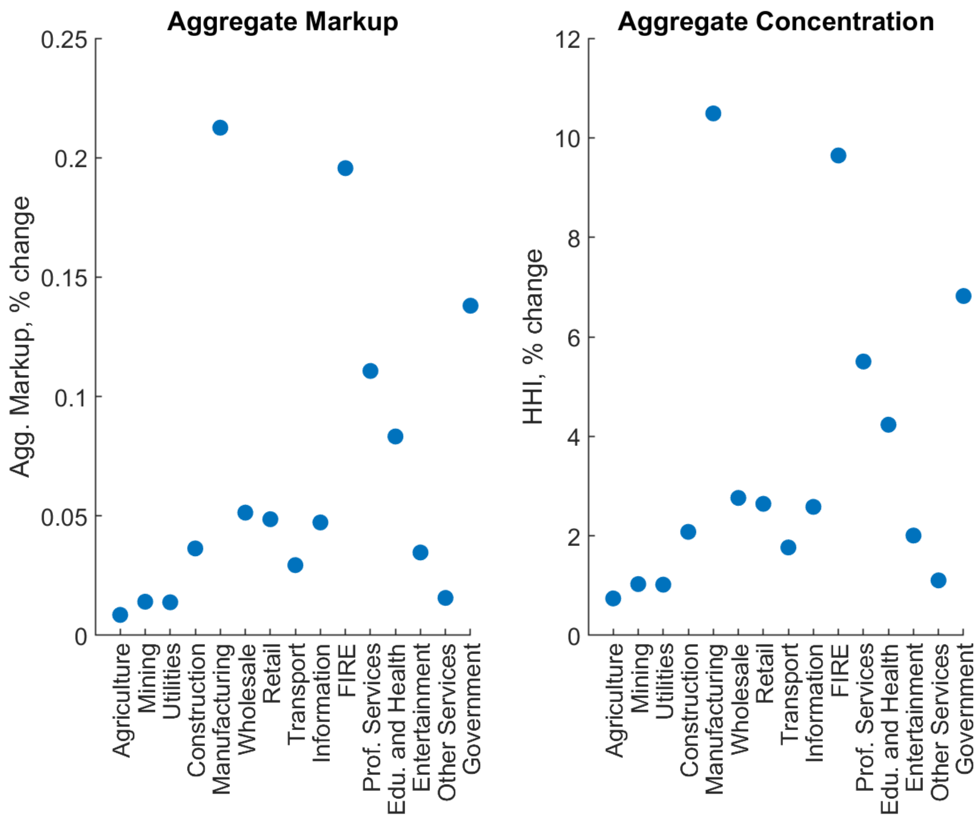
To sum up, the economy is calibrated to realistic targets from 2010, but by imposing sectoral homogeneity in all dimensions, except for the sector-specific sectors' sizes and I-O linkages. Sectors are hit by one-time permanent shocks. In the following, I present the economy right before and after the shock: the short horizon justifies why parameters are kept constant over time. In the simulation, I impose the same exact shock in each sector, where the first hits one sector at a time. This is to disentangle the sectoral heterogeneity in the propagation of sectoral shocks through the I-O structure.

6.2 Results

Section 4 suggests that the non-linearity embedded in the shock is first order to generate fluctuations in market power outcomes. By construction, a shock to ψ_{kt} affects disproportionately more the investment strategy of the firms that invest more and, no matter the presence or the lack of an inaction region, this alters the distribution of market shares. Ultimately, the shock impacts sectoral markups and concentration, and these effects propagate to the entire economy.

To translate this result to real-life scenarios, the relevant dimension of the platforms, at least through the lenses of this framework, is related to the range of services the firms have access to through the platforms themselves. Recalling the aforementioned case of Amazon, the decision of the company to introduce Prime and, then, Amazon Business Prime, hence allowing firms to choose their optimal investment strategy from a wider variety of possibilities (i.e. ψ_{kt} goes down), has a stronger impact on market power outcomes due to the change in dispersion rather than a change in the company's pricing strategy which lowers investment costs (i.e. ν_{kt} goes down).

Figure 17: Response of aggregate markup and concentration

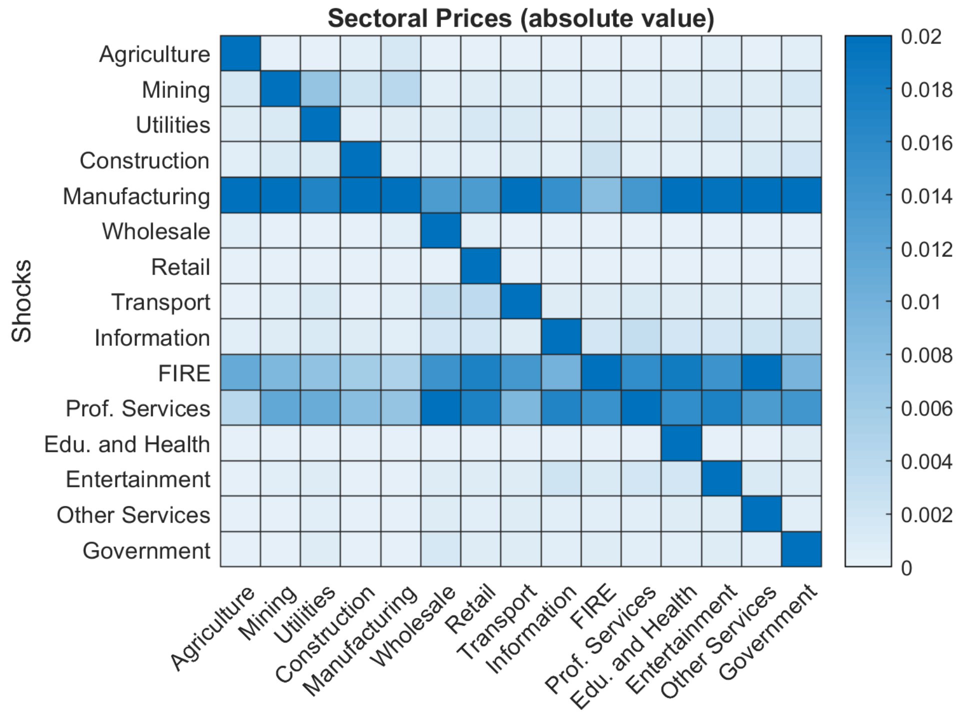


Notes: The graph plots the response of aggregate markups and concentration, in percentage points, to a sectoral shock that decreases ψ_{kt} by 20% in a given sector. The vertical axis represents the percentage change, while the x-axis the identifier of the sector in which the shock hits.

For this reason, in this section I focus on the effects of a permanent reduction to ψ_{kt} in a given sector, and study its effects on sectoral and aggregate outcomes. The experiment is the following: first, I solve the initial equilibrium for an economy calibrated as explained in Section 6.1, and where each sector shares the same value for both ν_{kt} and ψ_{kt}. Then, a permanent shock occurs in period t in sector k, which results in a 20% reduction in the curvature ψ_{kt}. Finally, I compute the new equilibrium for the economy, thus in period $t+1$, in response to the shock, and compare it to the initial scenario. This simulation in repeated 15 times, to allow the shock to hit each sector of the economy one by one.

Figure (17) shows the response of market power outcomes to the sectoral shocks to ψ_{kt}. For each sector reported on the x-axis, the corresponding blue dot represents on the y-axis the change in percentage points to aggregate markups and concentration generated by the shock to ψ_{kt} in that given sector. Clearly, larger and more connected sectors, as represented by the calibration of β_k, have the ability to affect the economy. In particular, Manufacturing and FIRE can generate a change in the aggregate markup approximately

Figure 18: Heat Map, Sectoral Prices, shock to ψ_{kt}



Notes: The heat map represents the response of sectoral prices, in percentage points, to a sectoral shock that decreases ψ_{kt} by 20% in one sector. Each row identifies the sector in which the shock occurs, while the columns the response of the respective sector. All responses are in absolute value.

equal to 0.2 percentage points, while reaching 10% for market concentration.

The effect on markup is economically small, but few considerations should be put forward: the simulation is plotting the period $t+1$-to-t change driven by a 20% reduction in the curvature ψ_{kt} in a sector only. If considering a longer time frame, it is not unreasonable to think that several shocks occur to both ν_{kt} and ψ_{kt}, as implied by the results in Section 5. This is consistent with the continuous introduction of new platforms in the last decade, as well as with the increase of the available range of services firms can subscribe to. Moreover, Figure (17) focuses on a single shock: a single change to the environment of the platforms, e.g. the launch of a new service by Amazon, is likely to affect multiple sectors at the same time, leading to a compound effect.

While the effects on aggregate markups and concentration are mainly driven by sectors' sizes, the underlying I-O structure magnifies the propagation of sectoral shocks to prices and quantities. Figure (18) plots the heat map for sectoral prices from this experiment. Each row represents the shocked sector, while columns describe the effects of the shock in the corresponding sector. To appreciate the heterogeneity in responses caused by the I-O structure, it is possible to compare this figure to the dynamics coming from the same study, but performed in an economy without I-O linkages.

In a model without linkages, the marginal cost is the same in each sector, and invariant to any shock, since it just reduces to the wage, always normalized to 1 in the simulations. Hence, it can be shown that sectoral allocations can be solved in isolation sector-by-sector, without the need of a fixed point algorithm: the distribution of market shares, which fully characterizes the equilibrium, boils down to the solution of a system of N_k equation in N_k unknown, i.e. each idiosyncratic market share.[63] Moreover, in each sector the distribution of market shares solely comes from the underlying distribution of productivity and implementation costs and the calibration of sectoral parameters.

All this considered, without linkages a shock to ψ_{kt} only impacts the sectoral price of the sector in which the shock realizes, while the remaining sectoral prices are unaltered.[64] Translating this to the graph in Figure (18), this would be represented by a null effect in all the off-diagonal elements of the heat map, with some action only on the diagonal entries. The magnitude of these dynamics depends on the strength of the firms' adjustments within each sector. Clearly, when considering the I-O structure, the response is totally different. Not only the sectoral prices are affected even if the shock occurs in a different sector, but there is a strong heterogeneity in the responses. For instance, the decrease in prices in Manufacturing has a larger impact on closely related sectors as Construction or Agriculture, where the prices drop substantially, while FIRE alters more the prices of similar service sectors like Information or Professional Services.

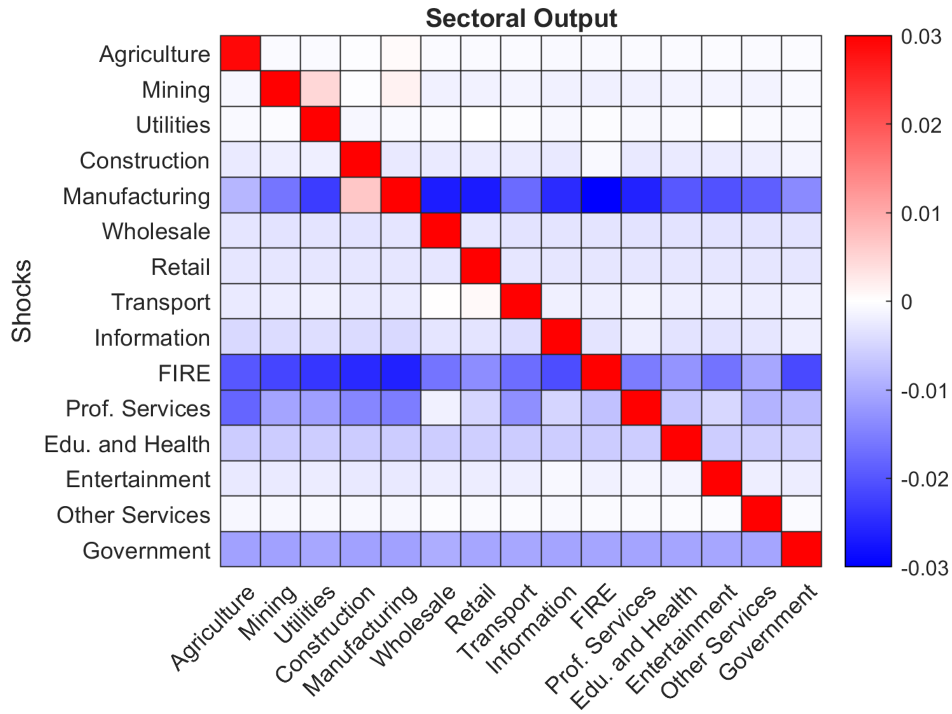
Figure (19) plots a similar heat map, but highlighting the effects on sectoral production. Again, the magnifying role of the I-O structure can be assessed by comparing these results to the ones from an economy without linkages. In the latter, heat is concentrated on the diagonal elements of the matrix. This happens because sectoral production is driven by the inverse of the relative sectoral price $\frac{P_{kt}}{P_t}$: in the sector in which the shock occurs the price goes down, and by more than the average, thus increasing production Y_{kt}. However, note that the aggregate price P_t moves as well in response to the shock, as the first is simply a weighted-average of the sectoral prices. Hence, even if the sectoral prices do not move in the sectors where the shock does not realizes, sectoral production does due to the increase in the relative price.

As for sectoral prices, the environment with I-O linkages is quite different from the scenario described above: the propagation is asymmetric, and some sectors show a smaller

[63]This occurs as both the optimal firm-level price p_{ikt} and the investment s_{ikt} are a function of the market share q_{ikt} and of exogenous parameters. The market share q_{ikt} simply depends on the idiosyncratic price p_{ikt} and on the sectoral price P_{kt}, a function of all the firm-level prices, and thus market shares, in the sector.

[64]This is true in the baseline model from Section 3. In the model from Appendix C, the shock has no effect at all, since there would be no investment without the I-O structure.

Figure 19: Heat Map, Sectoral Output, shock to ψ_{kt}



Notes: The heat map represents the response of sectoral production, in percentage points, to a sectoral shock that decreases ψ_{kt} by 20% in one sector. Each row identifies the sector in which the shock occurs, while the columns the response in the corresponding sector. Red squares describe positive changes, blue negative.

decrease in output than adjacent ones. For instance, the response to a shock in FIRE in Professional Services is weaker than the one in Manufacturing, since a decrease in the price of financial services lowers services' prices by more than goods'. Moreover, links between sectors can be so strong that even the sign of the response changes with respect to the situation without linkages. Due to the reliance on Mining in Utilities, or on Manufacturing in Construction, the prices of the second respond to a shock in the first to such an extent that their sectoral prices decrease by more than the average, resulting in an increase in the quantity produced. Overall, the inclusion of I-O linkages is crucial to understand the propagation of the shocks, both because of the asymmetry they create as well as for the magnitude of the response.

7 Sectoral Shocks

This section continues the analysis presented in Section 6, while allowing the shocks to ψ_{kt} to be sector-specific. The goal is to show that the heterogeneity in platform usage across sectors, proxied by a shock to ψ_{kt} calibrated to the patters of overhead spending, can be predictive of the heterogeneity in sectoral market power trends, in particular regarding sectoral markups.

7.1 Calibration

The calibration for the experiment follows. The calibration echoes the one presented in Section 6, while allowing more parameters to target sector-specific quantities, in order to improve the fit. As in the experiment from the previous section, parameters are kept fixed across time once calibrated. The only primitives that are allowed to change between the initial and final equilibria are the sector-specific investments costs parameters. In particular, $\psi_{kt} = 15$ and $\nu_{kt} = 5e - 4$ in the initial equilibrium in all sectors. Then, while keeping ν_{kt} constant, ψ_{kt} is shocked in each sector. Its calibration targets the change in the share of overhead costs over total costs observed empirically.

The idea behind this calibration is that, in the model, there is a correspondence between the total amount spent in the sector on overhead costs/subscription fees and the total investments in the platforms. Thus, I use the empirical variation in the first to discipline the sectoral heterogeneity in platform use in the model, through a shock to ψ_{kt}. Note that the calibration does not target the exact change in overhead shares in the data, by imputing the entire trend to a shock to ψ_{kt}, but it simply uses the relative patterns across sectors to rank the latter in terms of sign and magnitude of the shock. In other words, I first impose a baseline 10% reduction to ψ_{kt} in Manufacturing, and then I calibrate the shocks in the remaining sectors of the economy using the relative change in overhead cost shares across sectors.[65]

Regarding the remaining parameters, constant across time, the wage W_t is normalized to 1, while the GDP to 10000. The economy presents 15 NAICS-2 sectors, as presented in Sections 5 and 6. In the following, the targets use 2010 as the baseline year. The number of firms in each sector N_k is calibrated using Compustat. Under this calibration, the number of firms varies from few decades in Agriculture or Utilities to more than two thousands in Manufacturing. The BEA provides data on sectoral production and I-O linkages for 2010, which I use to calibrate the sector shares, β_k and the sectoral I-O linkages, through the sector-specific intermediate inputs elasticities ω_{Kj}.

For the elasticity of labor α_K, the BLS delivers data on the sectoral labor share, which is pinned down by the first. Again, sectoral variation is sizeable, ranging from a labor share of 0.21 in Mining to 0.7 in Professional Services. The elasticity of substitution

[65] Robustness checks with smaller baseline shocks in Manufacturing presents consistent results.

Table 7: **Calibration of the exogenous parameters**

Parameter	Value	Target
W_t	1	Normalization
Y_t	10000	Exogenous
N	15	Number of NAICS-2 sectors, BEA
N_k	[16 : 2052]	Sectoral number of firms, Compustat
β_k	[0.014 : 0.19]	Relative share sectors, BEA
θ	5	$\mu^{MC} = 1.25$, see Bernard et al. (2003)
α_K	[0.21 : 0.70]	Sectoral labor share, BLS
ω_{Kj}	[0 : 0.33]	Use Table I-O structure, BEA
$zmin$	1	Normalization
κ_ϕ	3	Granular heavy-tailed distribution
κ_a	7	Granular medium-tailed distribution

Notes: The table presents the calibration of the exogenous parameters for the experiment. When values are in squared brackets, parameters are calibrated at the sectoral level. Values in brackets represent the minimum and the maximum across sector. For the complete calibration see the replication package.

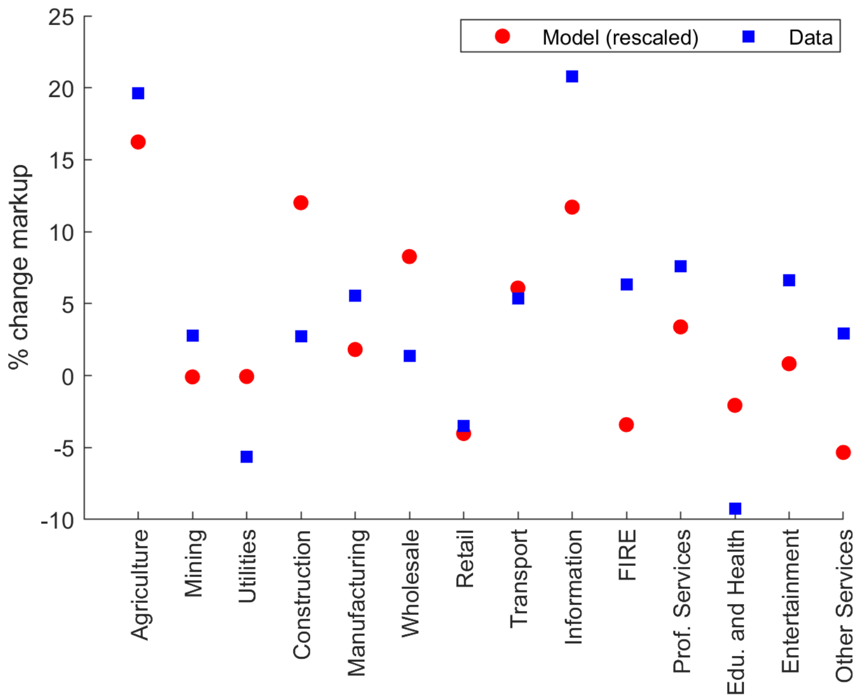
between goods θ is calibrated to 5 in all sectors, as in Section 6, and the parameters that discipline the underlying distributions of implementation costs and productivity follow the ones presented in the previous section as well. The parameters and their targets are summarized in Table (7).

7.2 Results

The results of the simulation are described in Figure (20). The figure shows the change in sectoral markups in the model, in red, and in the data, in blue. The empirical changes in markups shown echo the ones presented in Section 2: the differences plotted in blue represent the percentage deviations between 2010 and 1990 from Compustat. Note that the sectoral markups from the data are first detrended. Regarding the model counterparts, each observation is rescaled by multiplying by a factor of 10 to ease the visual comparison. In other words, if the red dot and the blue square are overlapping in a given sector, the model explains exactly 10% of the change in that sectoral markup in the data.

First of all, it is important to put forward that, in levels, the model underestimates the trends in sectoral markups observed empirically. Although this study can explain a sizable fraction of the pattern of sectoral markups in some selected sectors, e.g. more than 60% of the total increase in Wholesale and more than 40% in Construction, on average the model predicts approximately $5-10\%$ of the observed trends. Still, the main goal of the experiment is to explain the sectoral heterogeneity in these dynamics. Moreover, note that the levels are driven by the size of the baseline shock to Manufacturing, hence results are less robust, while the predictive power on the observed sectoral variation is unaffected.

Figure 20: Sectoral markups, sector-specific shocks to ψ_{kt}



Notes: The graph shows the change in sectoral markups in the model (red dots) and the data (blue squares). Regarding the model, to ease the visual comparison each observation is multiplied by 10, while the data presents the delta in markup trends over the horizon 2010-1990.

In the task of predicting the sectoral variation in market power trends, this experiment is more successful: the correlation between the changes in markups generated by the model and the patterns from the data counterparts is significant. Moreover, the sectoral variation in the percentage deviations of markups from the model can explain more than 40% of the sectoral heterogeneity in markups' trends observed in the data ($R^2 = 0.43$).

8 Conclusions

This paper studies the role of intermediary platforms as drivers for the observed trends in markups and concentration. The focus is both at the sectoral and aggregate level. E-commerce platforms introduced an extra margin in firms' decision problem: businesses can invest in the platforms to decrease their marginal costs, *trading* them with overhead costs. This allows more productive competitors to re-optimize their cost structure and exploit the opportunity to gain cost advantages, which turn into comparative advantages once they start to compete within their sector. This mechanism explains the increase in their market shares and markups, which lead the aggregate trends.

I present a theoretical framework with firm heterogeneity, I-O linkages, and oligopolistic competition that formalizes this trade-off. First, I show that, in a controlled theoretical setting, the key dimension is the non-linearity of the platform shocks: if the curvature of the investment cost function is decreased, thus reflecting a scenario in which the platforms start offering a wider variety of investment possibilities, high-investment firms benefit disproportionally more. This leads to an increase in the dispersion of the investment across firms, which affects the distribution of market power. Similar non-linear adjustments occur if the economy displays an inaction region, in which firms are optimally choosing not to invest, as *positive* platform shocks push some firms to opt in and start investing.

The model is brought to the data by calibrating the economy to 15 NAICS-2 sectors of the US, matching their relative sizes and sectoral I-O linkages. In the baseline study, the model predicts that 30 up to 45% of the increase in markups over the last three decades can be attributed to the rise of e-commerce platforms. Depending on the framework used, and on how the benefits of the investment are formalized, this welfare cost can be mitigated by an increase in aggregate productivity. Importantly, results show the importance of taking oligopolistic competition into account, since a model without this feature would underestimate the costs and overestimate the benefits of the rise in e-commerce platforms.

Next, I show that sector-specific platform shocks propagate to the entire economy, by affecting quantities and prices in all sectors. The I-O structure amplifies the transmission in magnitude, but even qualitatively in sign, with respect to an economy without linkages. Regarding market power outcomes, the propagation is milder, as shocks to the investment costs alter markups and, in particular, the market concentration of the sectors in which they occur. Still, larger sectors have the capacity to affect aggregate market power outcomes. Calibrating platform shocks to sector-specific targets, the model can explain up to 40% of the observed heterogeneity in market power trends across sectors.

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Appendix A

Markups are computed following the methodology outlined in De Loecker et al. (2020), based on the seminal work by Hall (1986). First, I assume that firms engage in a cost minimization problem by optimally adjusting a bundle of inputs with different degrees of flexibility. Under this setting, the ratio between prices and marginal costs, the markup, reduces to a product between two quantities: the inverse of the revenue share of the variable input and the elasticity of the variable input to output. In formula, the markup μ_{ikt} of a firm i, in sector k, in period t is:

$$\mu_{ikt} = \beta^v_{ikt} \frac{p_{ikt} y_{ikt}}{p^v_{ikt} v_{ikt}}, \tag{13}$$

where β^v_{ikt} is the output elasticity of the variable input, $p_{ikt} y_{ikt}$ the revenues, and $p^v_{ikt} v_{ikt}$ the variable costs.

Figure (21) presents 6 alternative measures for the aggregate markup, all based on specification (13). For each markup presented, the revenue share of the variable inputs has been computed using deflated sales ($SALES$ in Compustat) divided by the costs of goods sold ($COGS$). The presented estimates differ by the elasticity: in other words, all markups are in the form:

$$\mu_{ikt} = \beta^v_{ikt} \frac{SALES_{ikt}}{COGS_{ikt}}.$$

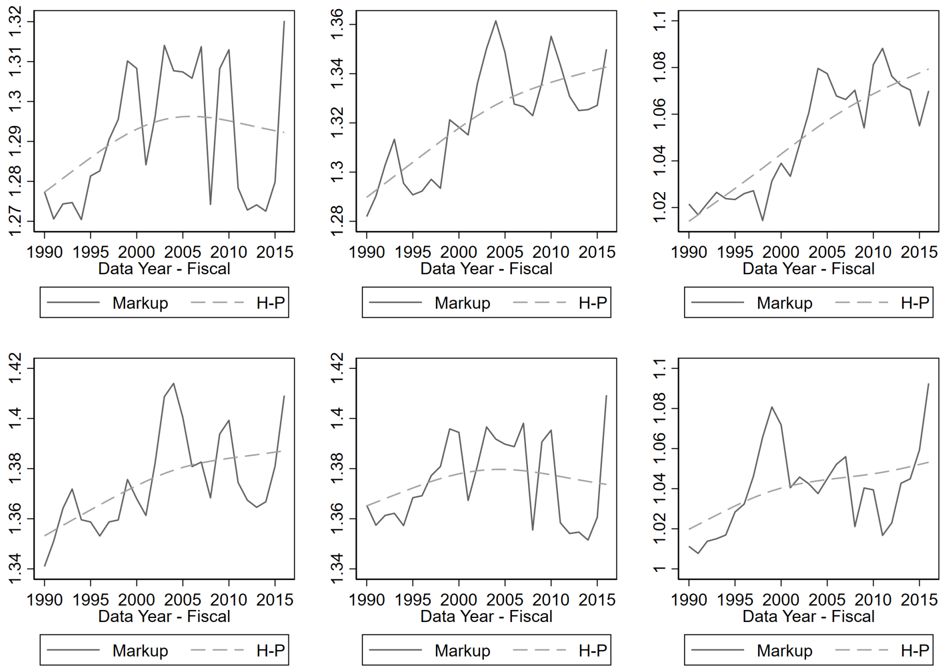
Markup 0 assumes a constant elasticity for each firm, which is equal to 0.85. In other words, $\beta^v_{ikt} = 0.85 \quad \forall i, k, t$. In markup 1, later used as the baseline specification, I pin down the elasticity using cost shares: the elasticity is the ratio between the costs of goods sold and the sum between $COGS$ themselves and capital expenditure. Markup 2 is the same, but also adding administrative expenses at the denominator ($XSGA$ in Compustat). These are the markups represented in the first row of Figure (21). Markup 5, represented in the left panel, second row, employs the specification from markup 2, but using sectoral averages for the elasticity instead of firm-level ratios. Finally, markups 11 and 13 extract the elasticity from a production function estimation at the sector and sector-time levels, respectively, see De Loecker et al. (2020) for details.[66]

Figure (21) presents six alternative measures for the aggregate markup, all based on the specification above.[67] Once markups are estimated at the firm-level, they are aggregated

[66] In the replication package, I collect 18 measures for the aggregate markups: the number corresponds to those specifications. The measures differ in the estimation of the elasticity, as above, as well as for the definition of the variable input share, e.g. by including a bundle of materials and labor as the variable input.

[67] In the replication package, I collect 18 markup measures for robustness, hence the number used to identify each specification in Appendix A. These indexes differ in the estimation of the elasticity, as well

Figure 21: Aggregate Markup, 6 Alternative Measures



Notes: The graph plots the evolution of the aggregate markup in the US over the horizon 1990:2016, together with the H-P filtered trend. Author's estimation based on the methodology outlined in De Loecker et al. (2020). Markups are estimated at the firm-level and, then, aggregated using a cost-weighted average. The description of each measure employed is presented in Appendix A.

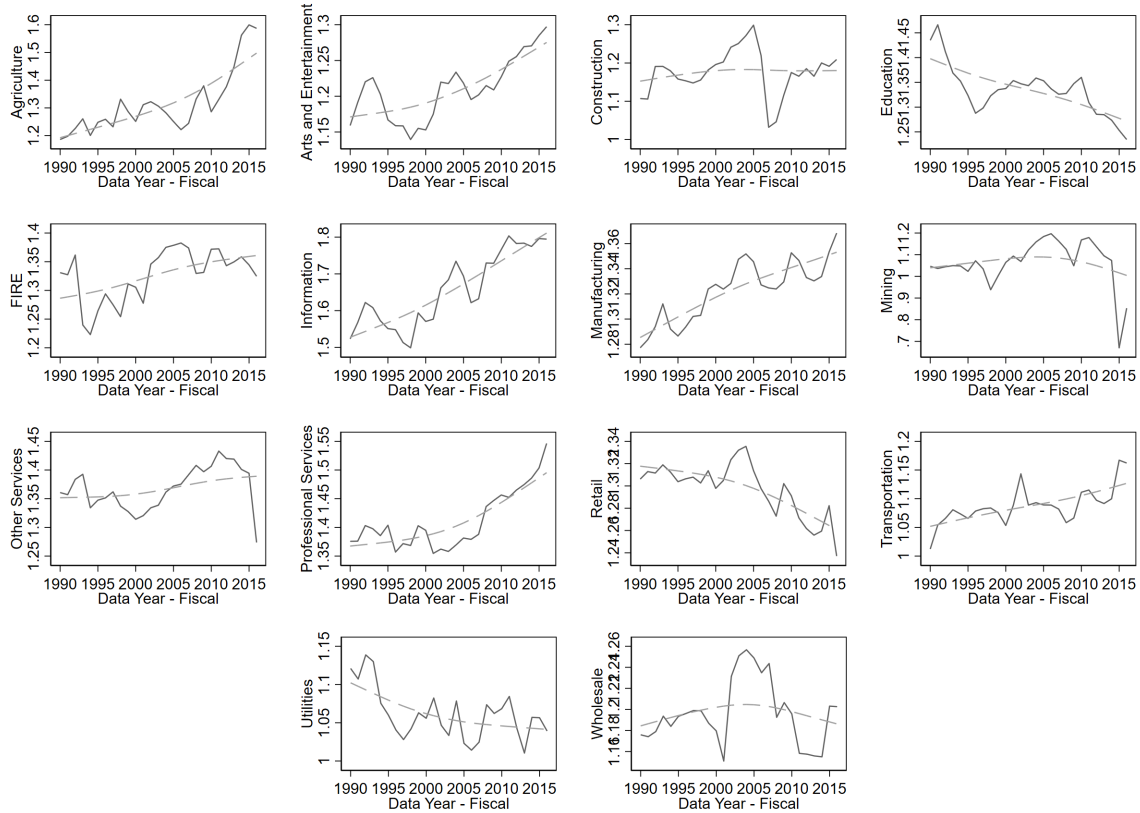
using a cost-weighted average, where the weights are represented by the ratio between the firm-level and the total costs of goods sold. Robustness checks extend the weights to capital expenditure, administrative expenses and materials, showing consistent results. This computation is repeated for each year to obtain the time series represented in Figure (21). Note that I use cost-weighted averages to compute aggregate and sectoral markups as they represent the welfare-relevant measures from the theoretical model.[68]

Figure (22) presents the sectoral markup for 14 NAICS-2 sectors of the US economy. The name of each (macro)sector is reported on the y-axes of the panels. The methodology for the estimation of the markups follows the one used in Figure (21). However, to keep

as for the definition of the variable input share, e.g. by using a bundle of materials and labor, or by including administrative expenses.

[68]The aggregator assumed in the model pins down the functional form of the aggregate/sectoral markups. In this framework, it implies that the sectoral markups are cost-weighted averages of the firm-level markups, or, equivalently, revenue-weighted harmonic averages. The difference between revenue and cost-weighted measures, and their relationship, is discussed in depth in Edmond et al. (2018). Moreover, van Vlokhoven (2021) shows that the increase in sales-weighted markups estimated in Compustat is driven by measurement error. On the other hand, the cost-weighted average is not affected by that measurement error and it is, thus, a more robust estimate of market power.

Figure 22: Sectoral Markups



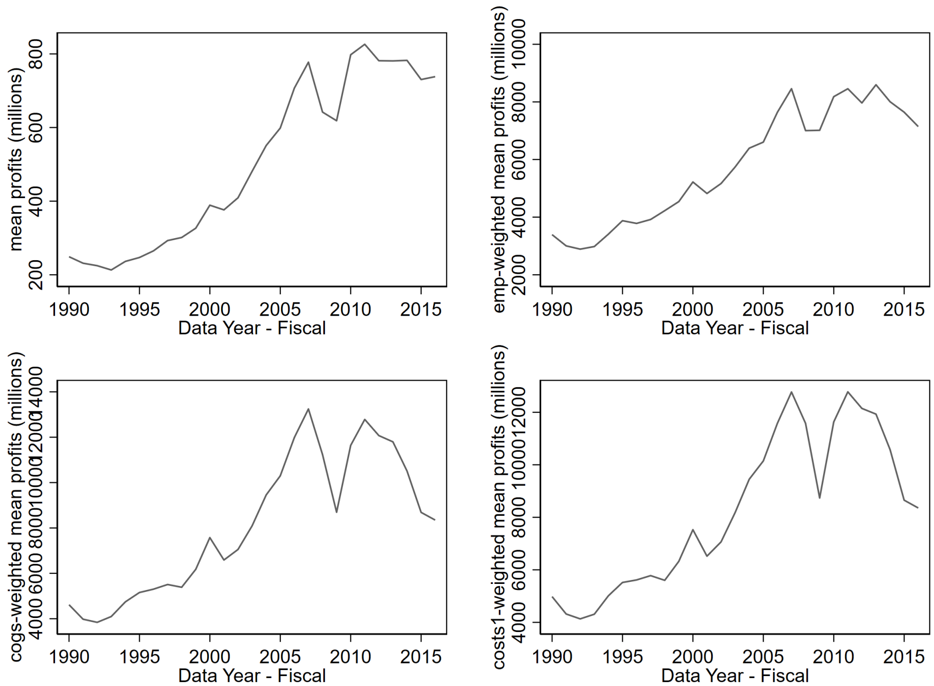
Notes: The graph plots the evolution of the sectoral markup in 14 NAICS-2 sectors of the US economy over the horizon 1990:2016, together with the H-P filtered trend. The sectors are, in alphabetical order, 1. Agriculture, 2. Arts and Entertainment, 3. Construction, 4. Education and Health, 5. Finance, Insurance, Real Estate (FIRE), 6. Information, 7. Manufacturing, 8. Mining, 9. Other Services, 10. Professional Services, 11. Retail, 12. Transportation and Warehousing, 13. Utilities, and 14. Wholesale. Author's estimation based on the methodology outlined in De Loecker et al. (2020). Markups are estimated at the firm-level with the baseline specification (measure 1 in Appendix A) and, then, aggregated using a cost-weighted average.

the figure readable, only the baseline specification is reported.[69] Markups are aggregated at the sectoral level with a cost-weighted average, where the weights are defined as the firm-level costs of goods sold ($COGS$ in Compustat) share over the total $COGS$ in a given pair sector-year.

It is clear from the panels shown in Figure (22) that sectors are characterized by a stark heterogeneity in markup trends: while some sectors mimic the aggregate economy by presenting a positive trend, others display a flat, or even decreasing, pattern. Hsieh and Rossi-Hansberg (2023), although focusing on a longer time frame, find a similar het-

[69]This is the specification number 1 in Appendix A, which is the baseline specification in De Loecker et al. (2020).

Figure 23: Aggregate Profits, 4 Alternative Measures



Notes: The graph plots the evolution of the aggregate profits in the US, over the horizon 1990:2016. The first panel presents the arithmetic average, the second the employment-weighted average, the third the cogs-weighted average and the last the costs-weighted average. In the latter, costs are defined as the sum between costs of goods sold and capital expenditure. Deflated values in millions dollars.

erogeneity for the change in sectoral market concentration.[70] Appendix B replicates the same study but for sectoral profits, showing consistent results.

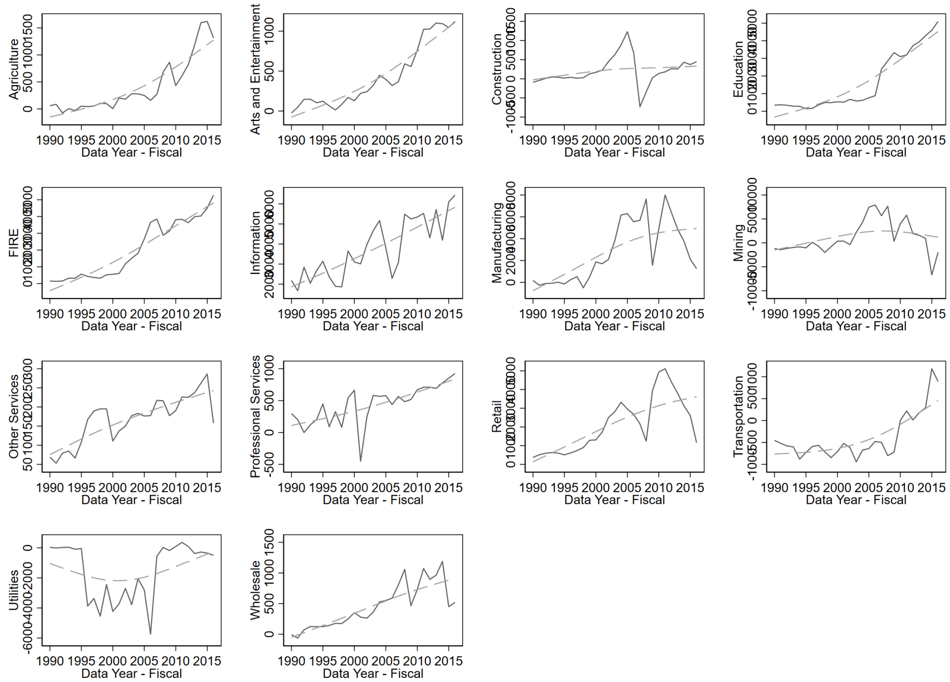
Appendix B

The following appendix complements the evidence shown in Section 2 for markups, presenting the results for aggregate and sectoral profits. Figure (23) shows the evolution of the aggregate profits in the US. In order to show the robustness of the result, the first panel plots the arithmetic average, the second the employment-weighted average, the third the cogs-weighted average and the last the costs-weighted average. As for the aggregate markups from Section 2, profits are increasing over time no matter the specification used, consistently with the evidence from the literature, see Grullon et al. (2019)

Figure (24) presents the same evidence but for sectoral profits. To show consistency,

[70]They claim that the change in the employment share of top firms from 1973 onward is mainly driven by three sectors: Wholesale, Services and Retail.

Figure 24: Sectoral Profits



Notes: The graph plots the evolution of the sectoral profits in 14 NAICS-2 sectors of the US economy over the horizon 1990:2016, together with the H-P filtered trend. The sectors are, in alphabetical order, 1. Agriculture, 2. Arts and Entertainment, 3. Construction, 4. Education and Health, 5. Finance, Insurance, Real Estate (FIRE), 6. Information, 7. Manufacturing, 8. Mining, 9. Other Services, 10. Professional Services, 11. Retail, 12. Transportation and Warehousing, 13. Utilities, and 14. Wholesale. Profits are estimated at the firm-level as in the model as: $(1-1/\mu_{ikt})REV_{ikt} - f^x_{ikt}$, where REV_{ikt} are the deflated revenues and the overhead costs are proxied by $XSGA$. Then, profits are aggregated at the sectoral-level using a cost-weighted average.

firm-level profits are computed here using the same functional form from the model: $(1 - 1/\mu_{ikt})REV_{ikt} - f^x_{ikt}$, where REV_{ikt} are the deflated revenues and the overhead costs f^x_{ikt} are proxied by $XSGA$. Sectoral profits display a stark heterogeneity across sectors, which mimics the one shown in the main text for sectoral markups.

Appendix C

This appendix extends the baseline model from Section 3, by allowing for alternative definitions of s_{ikt}. This variable represents the benefits of the investment in the platforms, where a higher investment leads to a *lower* s_{ikt}. First of all, whether s_{ikt} scales up output or it scales down costs, the allocation is the same: the first increases the benefits, while the second decreases the costs by the same amount. In other words, mathematically they result in the same F.O.C.s for the cost minimization problem, as well as for profits maximization. This is why results regarding market power outcomes are the same under both specifications.

However, the interpretation differs: if s_{ikt} scales down the costs, the investment describes a direct reduction of input prices. On the other hand, if s_{ikt} scales up the output, the investment represents efficiency gains. Thus, the firm is able to produce more due to the improvement in management practises, which decreases the waste of time and resources. This explains why measures of aggregate productivity differ between the two scenarios. Finally, note that both dimensions are true in the data: Forrester (2020) explicitly highlights the two as the main benefits of Amazon Business Prime.

Alternatively, the benefits could be modelled on output as an intermediate augmenting technology or, equivalently, by scaling down only the intermediate input costs. This alternative framework puts emphasis on the fact that the investment in the platforms originates from the underlying I-O structure: this is the model presented in this appendix. In formulas, the framework under scenario *a'* entails a factor $(s_{ikt})^{\alpha_K-1}$ on output, while, in scenario *b'*, s_{ikt} scales down only intermediates costs $\sum_{j=1}^{N} P_{jt}x_{ikt}^{j}$.

With respect to the baseline model in Section 3, differences are minimal: no matter the scenario, marginal costs are now scaled by $(s_{ikt})^{1-\alpha_K}$, hence the optimal price is:

$$p_{ikt} = \mu_{ikt}\frac{(s_{ikt})^{(1-\alpha_K)}}{a_{ikt}}\Xi_{kt},$$

while the optimal investment is:

$$s_{ikt} = \left(\frac{1}{1-\alpha_k}\right)^{\frac{1}{\psi_{kt}}}\left(\frac{\nu_{kt}\psi_{kt}}{\phi_{ikt}}\right)^{\frac{1}{\psi_{kt}}}\left(\frac{1}{Y_t\beta_k}\right)^{\frac{1}{\psi_{kt}}}\left[\frac{1+q_{ikt}(\theta-1)}{\left(\frac{1}{\theta}+2q_{ikt}\frac{\theta-1}{\theta}\right)q_{ikt}(\theta-1)(1-q_{ikt})}\right]^{\frac{1}{\psi_{kt}}}.$$

This alternative specification delivers the same qualitative results as the baseline, while quantitatively the dispersion of the investment is slightly reduced: the benefit is scaled here by a factor $1-\alpha_K$, instead of 1, since the abatement hits only a share $1-\alpha_K$ of the total variable costs. Hence, the incentive to invest decreases, while the costs are the same.

The replication package contains robustness checks in which all experiments are re-simulated under this alternative model, showing that results are consistent. In addition, as the only difference across models is the smaller and sector-specific dispersion, one could just re-calibrate downward the investment cost parameters ψ_{kt}: by adjusting the curvature in each sector by a factor $1-\alpha_K$, it is possible to obtain the allocation from the alternative specification in the baseline model as well. Alternatively, one could increase the thickness of the tail of the underlying distribution of ability ϕ_{ikt}, again restoring the same allocation in both settings.

Finally, note that the assumption of linearity in the main text can be justified by either (i) defining platforms more generally, hence including employment agencies that can ease the firing/hiring process, reducing labor costs, or (ii) by considering that platforms for intermediate inputs might impact labor costs, as the increase in efficiency results in less time wasted by the workers, with effects on the wage bill. To sum up, the baseline presents a more parsimonious specification, useful for its clarity and simplicity for exposition purposes, but alternative and, possibly, richer specifications deliver the same qualitative, and often quantitative, results.

Regarding aggregation, here the sectoral and aggregate markups share the same functional forms with the ones presented in the model from Section 3. In scenario *a'*, sectoral productivity is defined as:

$$Z_{kt} = \left(\sum_{i=1}^{N_{kt}} \frac{(s_{ikt})^{1-\alpha_K}}{a_{ikt}} \frac{y_{ikt}}{Y_{kt}} \right)^{-1},$$

while, under scenario *b'*:

$$Z_{kt} = \left[\left(\sum_{i=1}^{N_{kt}} \frac{(s_{ikt})^{1-\alpha_K}}{a_{ikt}} \frac{y_{ikt}}{Y_{kt}} \right)^{\alpha_K} \left(\sum_{i=1}^{N_{kt}} \frac{(s_{ikt})^{-\alpha_K}}{a_{ikt}} \frac{y_{ikt}}{Y_{kt}} \right)^{1-\alpha_K} \right]^{-1}.$$

Note that, if $\alpha_K = 1$, production is linear in labor. Thus, firms do not invest in the platforms, as intermediates are not needed in production. In this case, in both scenarios productivity reduces to an harmonic weighted average of firm-level TFP a_{ikt}. On the other hand, if $\alpha_K = 0$, the model is the same as in Section 3: given that no labor is used in production, a reduction of variable costs is equivalent to a reduction of intermediates costs. Indeed, sectoral production follows the functional forms for the two scenarios described in the main text.

Appendix D

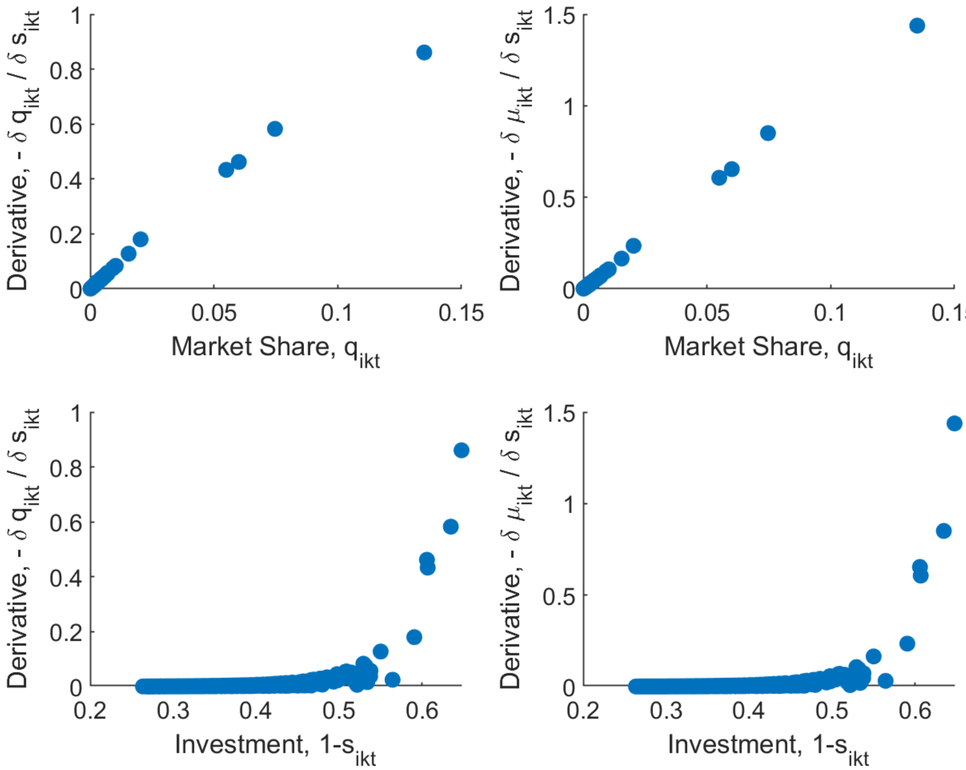
In this appendix, I present some key partial derivatives from the model in Section 3. First of all, it is useful to relate the market share, q_{ikt}, to the benefit of the investment, s_{ikt}. The derivative of q_{ikt} with respect to s_{ikt}, used in the main text to compute the optimal s_{ikt}, is:

$$\frac{\partial q_{ikt}}{\partial s_{ikt}} = -\frac{1}{s_{ikt}} \frac{q_{ikt}\left(1-q_{ikt}\right)\left(\theta-1\right)}{1+q_{ikt}\left(\theta-1\right)} < 0.$$

The derivative is negative as a higher s_{ikt}, i.e. a lower investment, results in a smaller market share. This derivative can be used to compute the change in markup, μ_{ikt}, with respect to s_{ikt}:

$$\frac{\partial \mu_{ikt}}{\partial s_{ikt}} = -\frac{1}{s_{ikt}} \frac{q_{ikt}\left(1-q_{ikt}\right)\theta}{1+q_{ikt}\left(\theta-1\right)} \left(\frac{1}{1-q_{ikt}}\right)^2 < 0.$$

Figure 25: Partial Derivatives



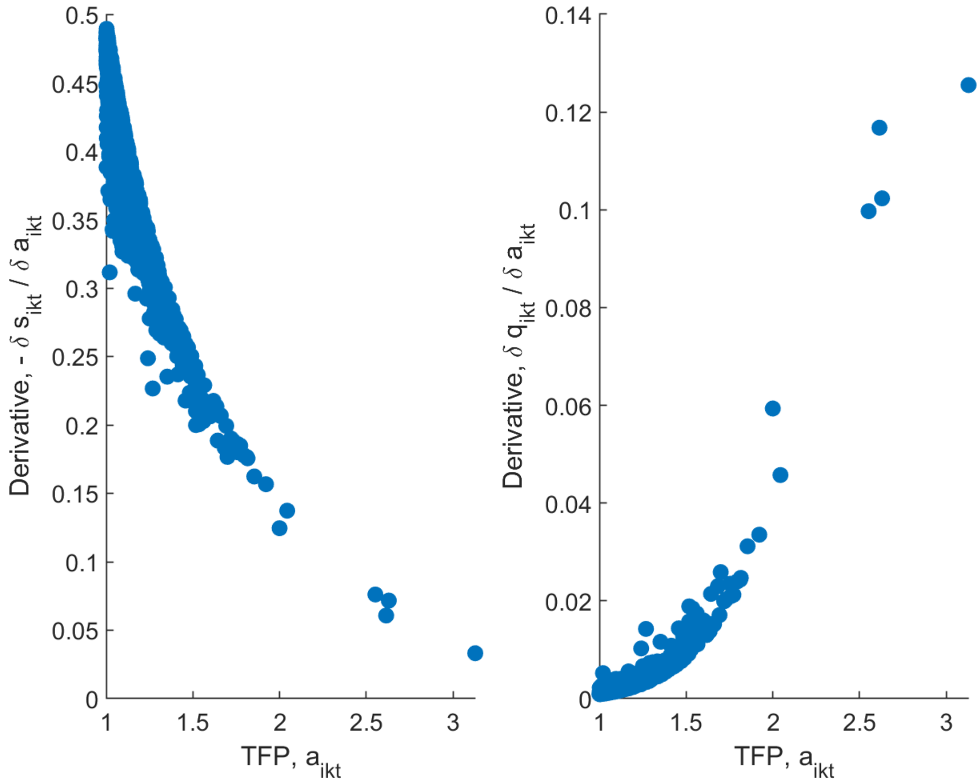
Notes: The graph plots the inverse of the derivative of q_{ikt} with respect to s_{ikt} (left panels) and the inverse of the derivative of μ_{ikt} with respect to s_{ikt} (right panels). The top row displays the partial derivatives as a function of the market share, the bottom row as a function of the investment, i.e. $1 - s_{ikt}$.

Again, the derivative is negative, given that a larger investment, resulting in a lower s_{ikt}, increases markups.

Figure (25) plots the partial derivatives described above. The series are computed as follows: first, I simulate a realization of the joint distribution of TFP and implementation costs for a large number of firms. Then, I solve the equilibrium for that distribution in a simplified economy, which is composed of a single sector with a roundabout in production. Once the equilibrium is found, I use that allocation to evaluate the derivatives for each firm in the economy. The same holds for Figure (26) below.

Left panels show the inverse of the derivative of q_{ikt} with respect to s_{ikt}, while the right panels the inverse of the derivative of μ_{ikt} with respect to s_{ikt}. To improve readability, I show the inverse of the derivative, i.e. $-\partial y/\partial x$. In this way, a positive value represents an increase in either q_{ikt} or μ_{ikt} to an increase in investment, meaning that s_{ikt} goes *down*. The top row displays the partial derivatives as a function of the market share, the bottom

Figure 26: Partial Derivatives with respect to TFP



Notes: The graph plots the inverse of the derivative of s_{ikt} with respect to a_{ikt} (left panel) and the derivative of q_{ikt} with respect to a_{ikt} (right panel) as a function of TFP, a_{ikt}.

row as a function of the investment, or $1 - s_{ikt}$.

The top panels show how an increase in investment is always related to an increase in market shares and markups. Moreover, the increase is stronger the larger is the market share: this echoes the known convexity of market shares with respect to a positive TFP shock in models à la Atkeson and Burstein (2008), as this one. A similar pattern emerges from the bottom panels: firms with higher investment benefit more from an increase in investment. In general, these findings are motivated by the fact that small low-investment firms are subject to the fierce competition of their peers. Thus, an increase in investment is not enough for them to emerge. Conversely, market leaders have more competitive space, and they are able to adjust their margins in response to shocks.

Next, I present the derivatives with respect to a_{itk}. These are non-trivial, as the mechanism is potentially counter-intuitive: when firms have shares above 50% of the market, their incentives are distorted and some derivatives change sign. This occurs as the firm is so large that any firm-level decision will affect sectoral quantities. An increase in the investment diminishes the individual price as well as the sectoral price. The second shrinks enough to disincentives firms' investment, as the lower sectoral price decreases the benefits of the firms. However, firms rarely get close to that margin, and in any example I present the derivatives are well behaved.

The derivative of s_{ikt} with respect to a_{ikt} is:

$$\frac{\partial s_{ikt}}{\partial a_{ikt}} = \frac{\frac{(\theta-1)\frac{q_{ikt}}{a_{ikt}}(1-q_{ikt})}{1+(\theta-1)q_{ikt}} \frac{s_{ikt}}{\psi_{kt}} [\chi]}{1 + \frac{(\theta-1)\frac{q_{ikt}}{\psi_{kt}}(1-q_{ikt})[\chi]}{1+(\theta-1)q_{ikt}}}$$

where:

$$\chi = \frac{2q_{ikt} - 1}{q_{ikt}(1-q_{ikt})} - \frac{\theta - 1}{(1+(\theta-1)q_{ikt})(1+2(\theta-1)q_{ikt})}.$$

The derivative of q_{ikt} with respect to a_{ikt} is:

$$\frac{\partial q_{ikt}}{\partial a_{ikt}} = \frac{\left[-\frac{\partial q_{ikt}}{\partial a_{ikt}}(\theta-1)\frac{q_{ikt}}{s_{ikt}}(1-q_{ikt}) + (\theta-1)\frac{q_{ikt}}{a_{ikt}}(1-q_{ikt})\right]}{1+(\theta-1)q_{ikt}}$$

Figure (26) plots the inverse of the derivative of s_{ikt} with respect to a_{ikt} (left panel) and the derivative of q_{ikt} with respect to a_{ikt} (right panel) as a function of TFP. As expected, an increase in TFP leads to an increase in investment, although the marginal change is decreasing in TFP itself: this happens as an increase in TFP is also reflected in an increase in market share. The benefits of the investment are increasing in the market share, as the same reduction in costs is enjoyed on a larger scale of production.

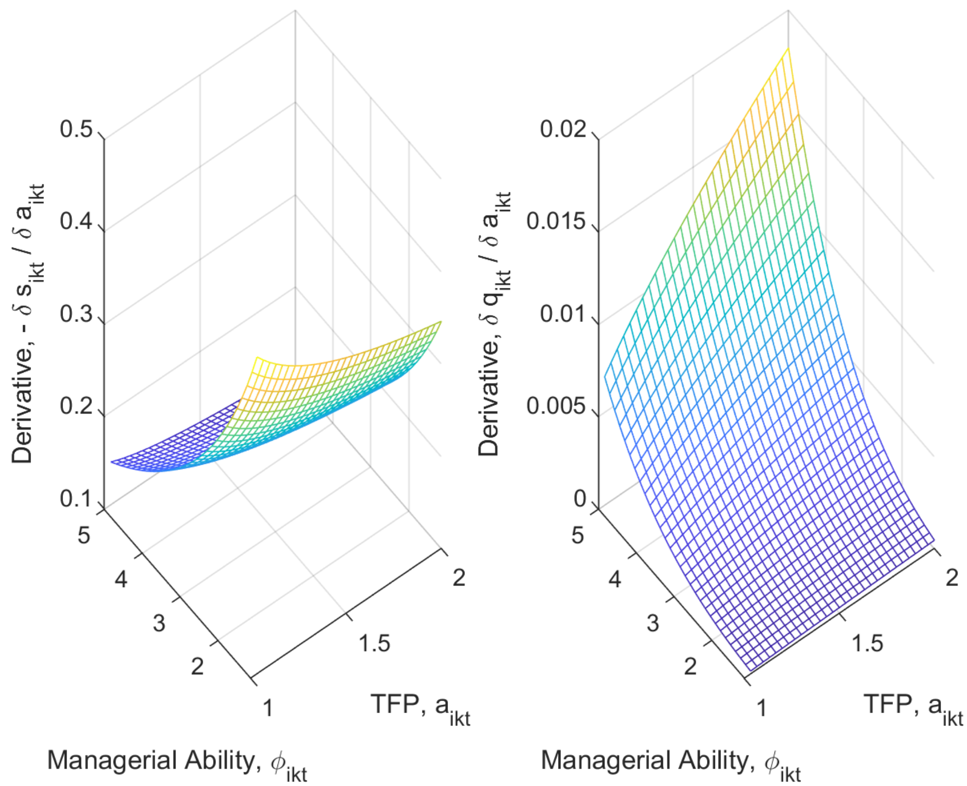
This explains why larger firms are more productive, charge higher markups, and spend more money in subscriptions fees with the platforms, consistently with the data on platform usage, see subsection 2.2, and on the correlation between overhead costs and markups, see subsection 2.1. Finally, Figure (27) plots the same derivatives in three dimensions, as a function of both TFP and implementation costs.

Appendix E

The following appendix presents the calibration used in the experiment below. With respect to the calibration in the main text, only few parameters are re-calibrated: the purpose of this second study is to show that results are robust to a richer environment.

To meet this goal, the number of firms is increased to $N_k = 578$ firms, which is the median number of firms from the Bureau of Economic Analysis (BEA) I-O tables for NAICS-4 sectors, see Grassi (2017), while the number of sectors is 10. Accordingly, Y_t is scaled to a value of 1000.

Figure 27: Partial Derivatives with respect to TFP and Ability



Notes: The graph plots the inverse of the derivative of s_{ikt} with respect to a_{ikt} (left panel) and the derivative of q_{ikt} with respect to a_{ikt} (right panel) as a function of TFP, a_{ikt}, and implementation costs, ϕ_{ikt}.

β_k is still calibrated to $1/N$ in all sectors, which here delivers $\gamma_Y = 10$, The same is true for the I-O structure: α_K, are fixed to a value of 0.56 for each sector, a calibration that reflects the median labor share from BEA, see Grassi (2017). The remaining elasticities of the production function, i.e. ω_{Kj}, which describe the I-O structure of the economy, are calibrated to $(1 - \alpha_K)/N$, such that constant return to scale holds. Note that this implies that $\zeta_{KY} = 5.47$.

The remaining parameters follows the ones in the calibration in the main text, and they are described in Table (8).

In the following, I present results for an environment in which all firms are investing in the platform, both before and after the shock. In other words, all the adjustments occur on the intensive dimension. Results change if an inaction region exists, where firms optimally choose not to invest. When this is the case, the shocks lead to adjustments both intensively and extensively, by altering the threshold for active investment behavior. This

Table 8: **Calibration of the exogenous parameters**

Parameter	Value	Target
W_t	1	Normalization
Y_t	1000	Exogenous, PE model
N	10	Number of sectors
N_k	578	Median number of firms BEA, Grassi (2017)
β_k	$1/N$	Symmetric sectors
θ	5	Standard, $\mu^{MC} = 1.25$, see Colciago and Silvestrini (2022)
α_K	0.56	Median labor share BEA, Grassi (2017)
ω_{Kj}	0.044	CRS and symmetric I-O structure
$zmin$	1	Normalization
κ_ϕ	3	Granular heavy-tailed distribution
κ_a	7	Granular medium-tailed distribution

Notes: The table presents the calibration of the exogenous parameters for the experiment.

second scenario in presented in subsection 4.2.

Intensive Adjustments

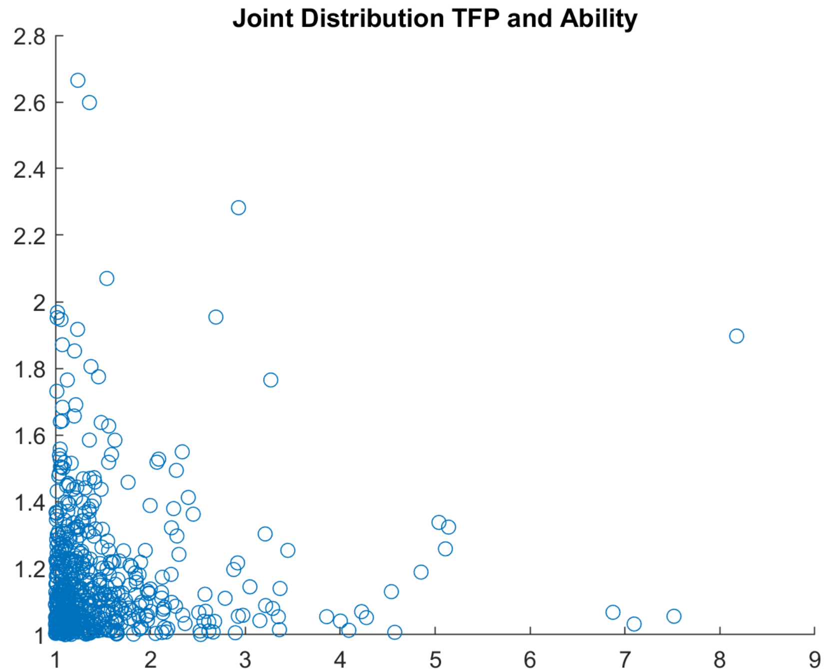
Figure (28) represents the joint distribution of firm-level productivity a_{ikt} and implementation costs ϕ_{ikt}. This distribution is simulated once and kept constant across sectors to allow for comparisons and disentangle the effects of the shocks.

Given that the two distributions are *ex ante* independent, it can be noticed how the majority of firms presents a relatively small TFP and ability, while only few are endowed with high TFP (y-axis) or extreme ability (x-axis), and rarely both. The Pareto distribution for ability presents a ticker tail than the one for TFP, and this explains why firms are more extreme on the first dimension.

Figure (29) presents the distribution of individual investment for a simulation in which the 10 sectors of the economy are initially homogeneous and symmetric. This is the baseline used as the initial environment. Then, the two investment cost parameters are shocked to asses their impact on market power dynamics. Figure (30) presents the scenario in which sector 1, and this sector only, is hit by a shock that raises ν_{kt}. Figure (30) depicts a similar picture, but for a permanent increase in ψ_{kt}. After comparing the micro-level investment behavior, I show the results for sectoral markups and concentration.

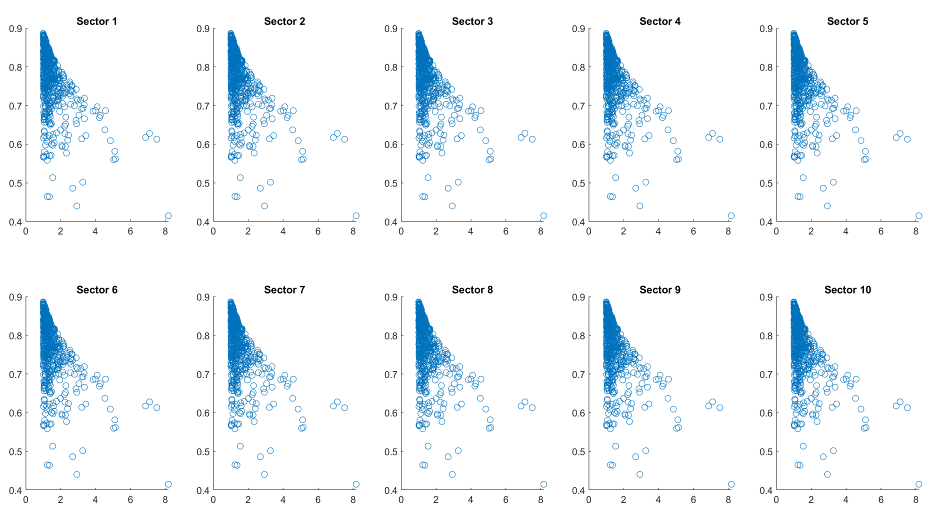
Not surprisingly, since sectors are completely homogeneous, the distribution of investment is the same across sectors. As mentioned before, note that, although the magnitude oscillates significantly, each firm is investing a positive amount. The dispersion in investment, together with the variation in firm-level TFP, is responsible for the observed heterogeneity in market power. In this baseline initial environment, the sectoral markup

Figure 28: Distribution of implementation costs and productivity.



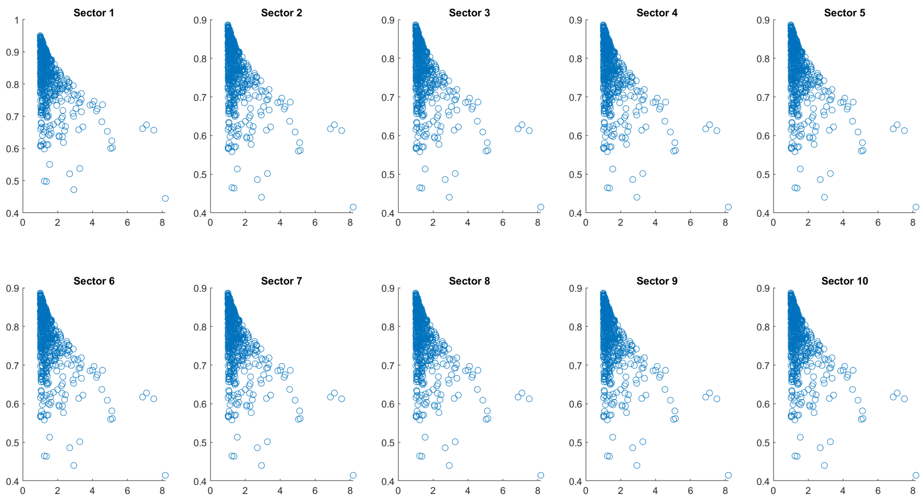
Notes: The graph plots the joint distribution of TFP and ability. This distribution is simulated once and kept constant across sectors. Firm-level productivity a_{ikt} is represented on the y-axis, while implementation costs ϕ_{ikt} on the x-axis, and each dot describes a firm.

Figure 29: Initial distribution of sectoral investment



Notes: The graph plots the distribution of investment in each sector. Initial scenario: sectors are homogeneous and symmetric. Each dot represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic ϕ_{ikt}.

Figure 30: Final distribution of sectoral investment, shock to ν_{1t}



Notes: The graph plots the distribution of investment in each sector. Final scenario: sectors are homogeneous and symmetric, except for ν_{kt} which is higher in sector 1. Each dot represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic ϕ_{ikt}.

is 1.286, the dispersion of firm-level markup 0.0091, and the Herfindal Index 0.028.

Figure (30) shows the results for a change in the common cost component in sector 1.[71] The individual investment decision is clearly altered by the shock. In particular, the distribution moves up uniformly as ν_{1t} increases, meaning that each firm invests less than before.

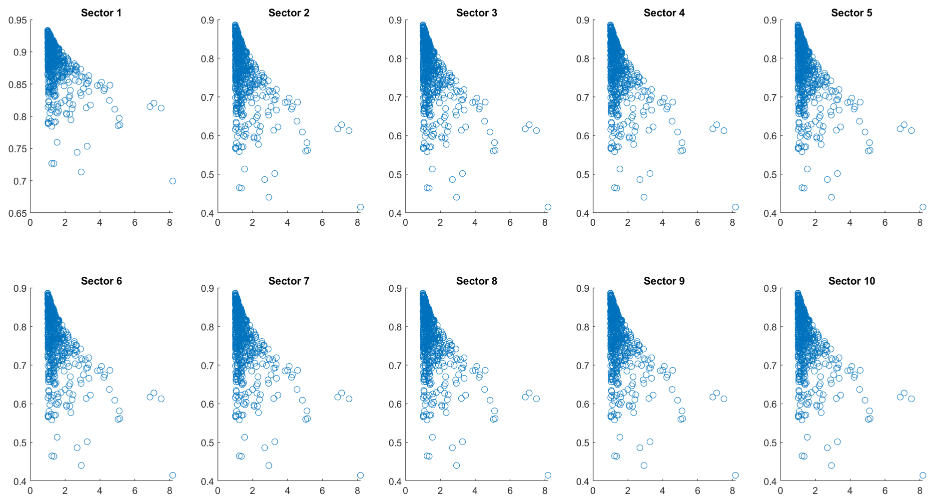
In the sector, the variation in total investment changes the average marginal cost and, in turn, the sectoral price P_{1t}: as ν_{kt} doubles, the sectoral price experiences a 7.8% increase with respect to the baseline. Moreover, the total production of sector 1 shrinks by 6%, due to the increase in the relative price of good 1.

Thanks to the I-O structure, the shock indirectly propagates to the remaining sectors of the economy, although they do not experience the shock directly. This can be seen by observing sectoral prices, marginal costs and productions, which show that the magnitude of the transmission is not negligible: prices increase by 0.5% and marginal costs by 0.6% in the other sectors, while the output increase by 0.7%. Finally, note that the transmission of the sectoral shock is strong enough to affect the aggregate, as the aggregate price index P_t displays a 1% increase.

However, comparing the different sectors, it can be seen that sector-1 firms react proportionally in such a way that the relative size distribution is unaffected: the distribution

[71] To highlight the shock, I impose a 100% increase to ν_{1t} with respect to the initial scenario. The same magnitude is kept for the shock to ψ_{1t} below, as well as in subsection 4.2.

Figure 31: Final distribution of sectoral investment, shock to ψ_{1t}



Notes: The graph plots the distribution of investment in each sector. Final scenario: sectors are homogeneous and symmetric, except for ψ_{kt} which is higher in sector 1. Each dot represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic ϕ_{ikt}.

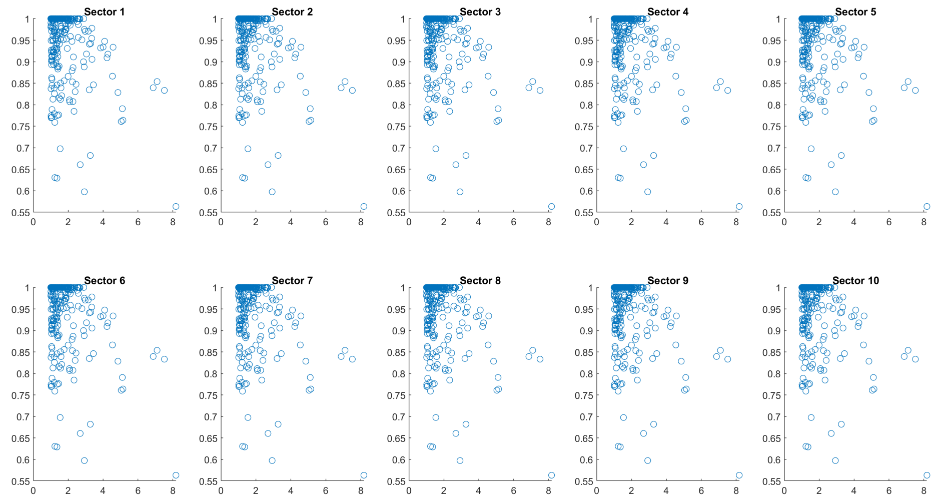
of investment moves up, without affecting the relative gap between the firms. Since the distribution of market shares is unaltered, sectoral markups and concentration do not move: the HHI, sectoral markup and markup dispersion are equal in all sectors, and exactly the ones from the initial scenario. In other words, in this environment the main indexes of sectoral market power are invariant to a shock to ν_{kt}.

These dynamics are significantly different if the perturbation targets the curvature of the cost function, as shown by Figure (31). The relative effect of an increase in the sector-specific curvature ψ_{kt} is larger for top-investment firms, as their exposure to the shock is higher. In particular, the first panel shows that not only the distribution moves upward, as for the shock to ν_{kt} in Figure (30), but the dispersion shrinks considerably. In other words, each firm is reducing its own investment, as before, but firms that investment a large amount shrink relatively and absolutely more.

On top of the aforementioned propagation of the shock through the I-O structure, present in both specifications, the intensive adjustment in relative investment behavior affects the distribution and dispersion of market shares, differently from the previous experiment. These non-linear firm-level adjustments drive the observed response in markups and concentration. In particular, in sector 1 the Herfindal index decreases by 64% and the sectoral markup decreases by 2%, with a reduction of 45% in firm-level markup dispersion.

To sum up, whenever all firms are actively investing through the platform, any shock to the level of the investment cost ν_{kt} trigger strong adjustments in prices and quantities that

Figure 32: Initial distribution of sectoral investment



Notes: The graph plots the distribution of investment in each sector. Initial scenario: sectors are homogeneous and symmetric. Each dot represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic ϕ_{ikt}.

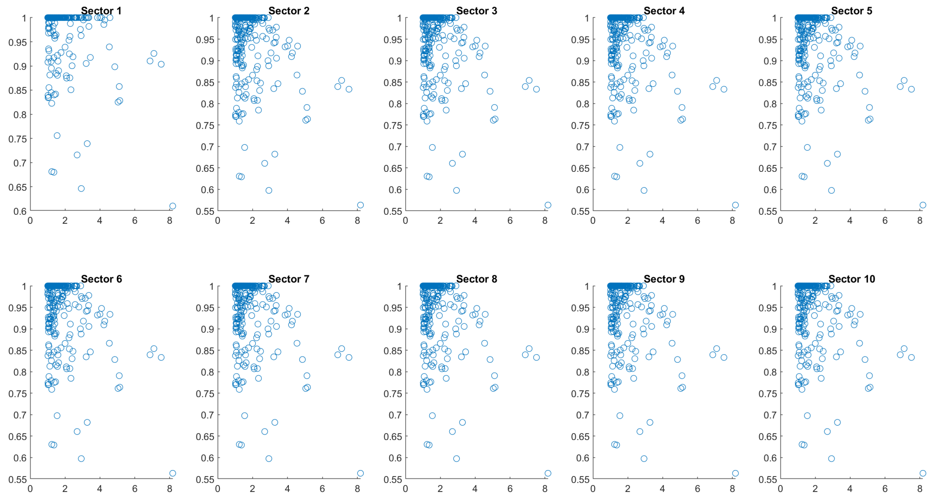
propagate to the rest of the economy. However, the shock is absorbed in its entirety by the price, and market power indexes are unaffected. This changes if the perturbation hits the curvature parameter ψ_{kt}, as the shock alters the distribution of markups and market shares.

Intensive and Extensive Adjustments

This subsection reproduces the simulation above for a slightly different environment. Figure (32) presents the result for a simulation in which the 10 sectors of the economy are initially homogeneous and symmetric. This is similar to the baseline used as initial environment in Figure (29). However, here the initial value of ν_{kt} is increased such that an inaction region emerge: below a certain threshold, function of ϕ_{ikt} and a_{ikt}, firms decide to invest no resources in the platform, i.e. $s_{ikt} = 1$. If this is the case, their variables are solely driven by idiosyncratic productivity a_{ikt}.

As in the previous section, I compare this initial scenario to the equilibria that emerge when the two investment cost parameters are shocked. Figure (33) presents the scenario in which sector 1, and this sector only, is hit by a shock that raises ν_{kt}. Figure (34) depicts a similar picture, but for a permanent increase in ψ_{kt}. In relative terms, the percentage increase in the two parameters is the same as in subsection 4.1, although the levels are different.

Figure 33: Final distribution of sectoral investment, shock to ν_{1t}



Notes: The graph plots the distribution of investment in each sector. Final scenario: sectors are homogeneous and symmetric, except for ν_{kt} which is higher in sector 1. Each dot represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic ϕ_{ikt}.

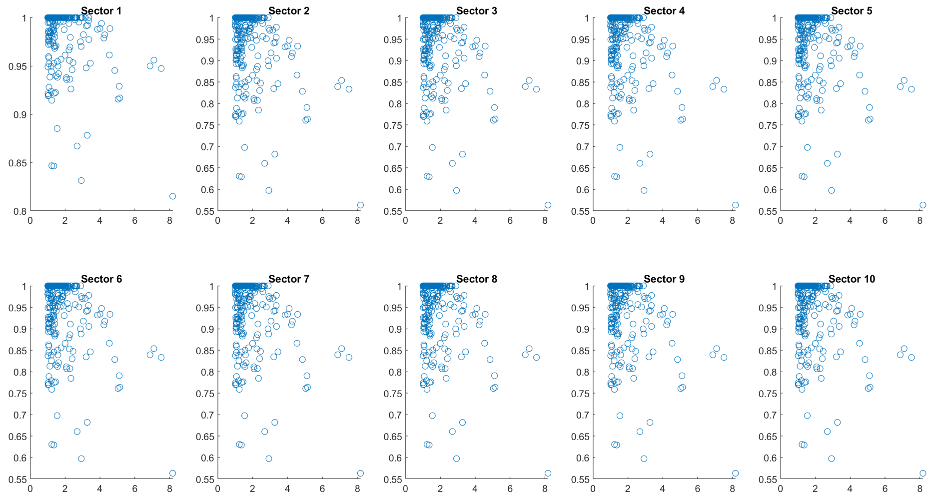
For this new baseline, the sectoral markup equals 1.282, with a dispersion of firm-level markup of 0.0086, while the HHI is 0.025.

Differently from the previous simulation, the change in the cost parameter ν_{kt} triggers two types of adjustment: on the intensive margin, each firm reacts to the shock by re-optimizing its investment, with the effects on prices and quantities described above. Graphically, this moves the distribution upward, representing an uniform decline in investment among active firms.

On the extensive margin, the shock to the investment costs moves the threshold. Given that, in this case, ν_{1t} increases, some firms optimally choose to stop their investment. This can be inferred from the graph: the fact that investment has an upper bound in 1 means that the distribution hits a plateau when shifting upward. This affects the relative adjustments between firms since, while some firms are free to change their investment behavior, other are already at or around the minimum, and, hence, the shock has no effects on these firms. In other words, a uniform increase in ν_{1t} does not have the same impact on all firms.

Because of this reason, here a shock to ν_{kt} carries non-negligible affect on market power outcomes: the HHI decreases by 15%, while the sectoral markup by 0.5%, with a 9% reduction in firm-level markup dispersion. Moreover, note how, due to the fact that part of the shock is absorbed by the markups, prices and quantities in sector 1 react less with respect to the case discussed in the previous subsection (approximately, their response

Figure 34: Final distribution of sectoral investment, shock to ψ_{1t}



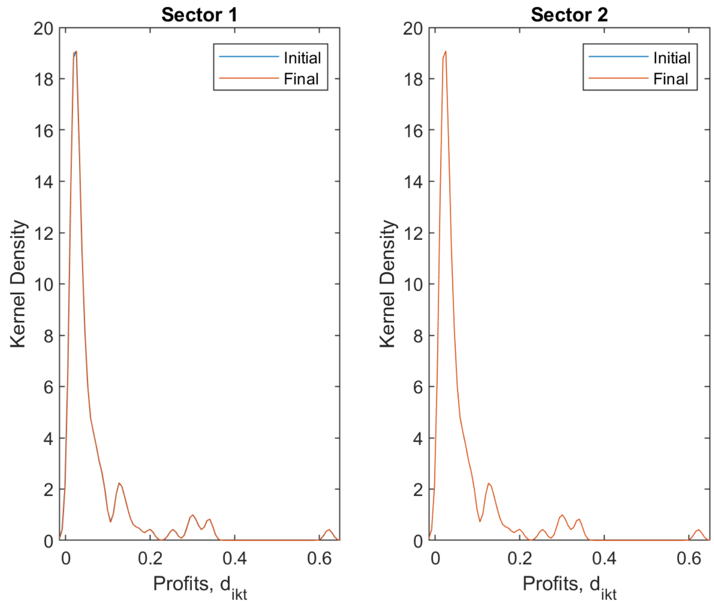
Notes: The graph plots the distribution of investment in each sector. Final scenario: sectors are homogeneous and symmetric, except for ψ_{kt} which is higher in sector 1. Each dot represents a firm, where the y-axis represents investment, while the x-axis the idiosyncratic ϕ_{ikt}.

is muted by one percentage point).

Figure (34) present the results for the simulation where sector 1 experiences a sudden increase in ψ_{1t}. Results are quite similar to the case discussed in subsection 4.1: prices and quantities are altered in sector 1, and the shock propagates to the entire economy. Moreover, due to the non-linear intensive adjustments motivated by the different exposure to a second-moment shock, the distribution of market shares within sector 1 is affected, with noticeable effects on the sectoral markup and concentration.

Comparing the results with the previous scenario, the presence of extensive adjustments does not alter the impact of the shock on market power outcomes: although the shock carries no effects for inactive firms, and the effect is mitigated for firms close to the threshold, the sectoral effects are almost solely driven by the top firms. Firms that invest large amounts with the platforms or that, more in general, display large market shares matter disproportionally more for the sectoral market power outcome. As their adjustments are not affected to a first order by the presence or the lack of an inaction region, since firms in that region are not direct competitors of the market leaders, the effects of the shock to ψ_{kt} in the two scenarios is similar.

Figure 35: Distribution of profits, pre and post shock to ν_{1t}

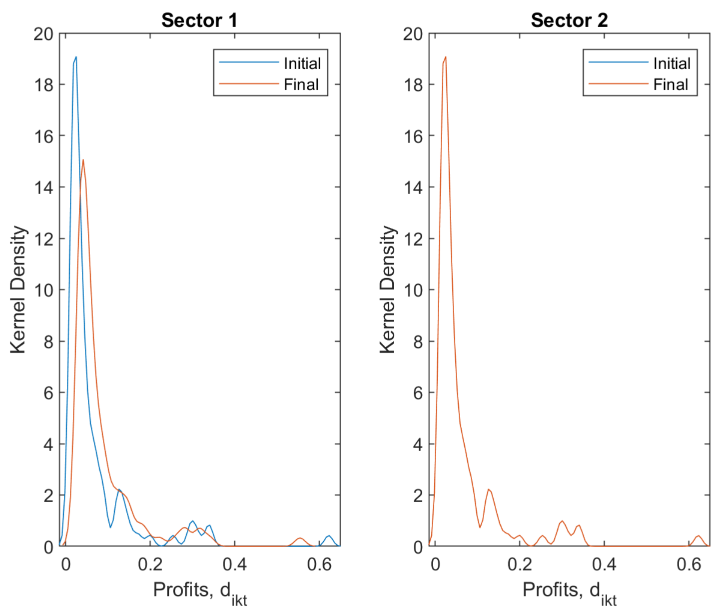


Notes: The graph plots the kernel distribution of firm-level profits in each sector. Initial scenario, blue lines: sectors are homogeneous and symmetric. Final scenario, red lines: sector 1 only experiences a permanent increase in ν_{kt}.

Appendix F

This appendix reports the distribution of firm-level profits from the experiments presented in Section 4.

Figure 36: Distribution of profits, pre and post shock to ψ_{1t}



Notes: The graph plots the kernel distribution of firm-level profits in each sector. Initial scenario, blue lines: sectors are homogeneous and symmetric. Final scenario, red lines: sector 1 only experiences a permanent increase in ψ_{kt}.