Technology Equalizers: How Digital Platforms Level the Playing Field for Small Firms*

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Abstract

We study how platform technologies differentially impact the productivity of smaller firms. Platforms reduce a broad range of costs of coordinating and motivating transactions: the cost of processing information, of matching and reaching customers, of informational asymmetries, and of completing and enforcing contracts. Our theory suggests that, by reducing transaction costs, platforms allow firms to replace high fixed cost, low variable cost technologies (insourcing) by low fixed cost, high variable cost technologies (outsourcing). Using data from the European Investment Bank Investment Survey (EIBIS), we find that digital platform adoption is associated with increases in labor productivity of 3.4% to 5.1% on average, with smaller firms experiencing a larger increase of 6.5% to 10.5%. Our results are robust to controlling for endogeneity by using instrumental variables (US adoption rates in the same sector and regional internet speed) in a three stage estimation procedure (since adoption is a binary variable). We conclude that while the large physical and human capital requirements of IT investments favor large firms and lead to industry concentration, digital platforms can level the playing field by facilitating the access of smaller firms to these same technologies through the market.

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1. Introduction

Multisided platforms facilitate exchanges and interactions between different types of users (Parker and Van Alstyne, 2005; Kretschmer et al., 2022; Rochet and Tirole, 2003), such as buyers and sellers (Rietveld et al., 2019; Cennamo and Santalo, 2013), businesses finding suppliers (Nicoletti, 2020), or workers seeking employment with firms searching for candidates (Gu and Zhu, 2021). These platforms have existed in the physical world for centuries – consider medieval trade fairs as in Fishman and Sullivan (2016) – but digitalization and the internet have significantly amplified their emergence and importance. By reducing the need to travel to a central location, digital platforms make interactions possible also through mobile applications. As a result, they have reduced transaction costs, alleviating information asymmetry, and diminishing coordination costs (Garicano and Kaplan, 2001).

Despite the substantial efficiency gains that platforms can offer, not all firms benefit equally, nor do all firms adopt them (Greve and Song, 2017; Brynjolfsson et al., 2006; Oberholzer-Gee and Strumpf, 2007). In this paper, we investigate this disparity and argue that, like all outsourcing decisions, the use of standardized solutions provided by platforms involves a trade-off between fixed and variable costs (Loertscher and Riordan, 2019).[1] Large firms can adopt customized solutions through significant fixed investments in physical and human capital, while small firms are unable to sustain such investments. Small firms can obtain standardized products and services in the market, through outsourcing. Of course, outsourcing involves higher (market) transactions costs (Arrow, 1969; Williamson, 2008). Recent advances in platform technologies have increased the viability of these high variable cost/low fixed cost solutions by reducing market frictions (Boudreau and Hagiu, 2009; Chu and Wu, 2023).

The reduction in market frictions affects both the cost of coordinating transactions and of solving the incentive and commitment problems that impede transactions.[2] First, platforms reduce *coordination costs* through process improvements, as platforms automate tasks, streamline information processing, and integrate advanced technologies like AI (Cennamo, 2018; Chatain and Mindruta, 2017; Chatain and Zemsky, 2011; Gupta et al., 1999; Katz and

[1] We do not address issues related to platform market power abuses or user harms as regulated by the European Digital Markets Act and Digital Services Act. Although these concerns are important, they are beyond the scope of this paper.

[2] To classify the gains in transaction costs, we use the framework of Milgrom and Roberts (1992) as developed in Garicano and Kaplan (2001). As Milgrom and Roberts (1992) acknowledge, the line between transaction and production costs is sometimes not entirely clear. We nevertheless find the categorization useful.

Shapiro, 1985). For example, Amazon Web Services offers scalable IT infrastructure in a way that is cost-effective for small firms. They also reduce search and matching costs to expand market reach and improve transaction efficiency (Chatain and Mindruta, 2017; Chatain and Zemsky, 2011; Stallkamp and Schotter, 2021; Hortaçsu et al., 2009). For instance, adtech platforms like Google Ads and Meta Business Manager enable targeted global advertising; e-commerce platforms like Amazon and Zalando facilitate global sales; LinkedIn and other job platforms provide small firms with access to global talent.

Second, platforms also reduce *motivation and incentive costs*, in two ways. First, they reduce informational asymmetries: platforms with user reviews like Tripadvisor and Yelp help small firms build online reputation, reducing the need for established brands (Chu and Wu, 2023; Pavlou and Gefen, 2004; Ter Huurne et al., 2017). Second, reservation platforms like Airbnb and Booking.com enforce standardized contracts and offer dispute resolution, reducing the cost of making and committing to contracts (Hagiu, 2014, 2009).

We propose a simple analytical framework to study the impact of these reductions in transaction costs due to improvements in platform technology on firms of different sizes. Our model examines firms with heterogeneous productivity that face a downward sloping demand curve and choose between two technologies: outsourcing (lower fixed costs, higher variable costs) or insourcing (higher fixed costs, lower variable costs) with a dual production function as in Poppo and Zenger (1998). We show that firms below a productivity threshold outsource, while those above it insource. The reason is that insourcing involves building capabilities (e.g., IT, talent) that reduce variable costs, and this only makes sense for firms above a certain size – those that are more productive. Conversely, outsourcing leverages external services, raising variable costs but reducing initial investments.

Our analysis yields two main results: Proposition 1 shows formally that there exists a productivity threshold such that firms above that threshold insource, and those below it outsource. Proposition 2 shows that reduced transaction costs through platform technology result in increased measured productivity, reduced prices, and increased output for smaller firms, as well as a higher productivity threshold for bringing production in house.

We then extend the model to the case where demand is stochastic. When demand can drop to zero with probability q, variable costs are avoided, but fixed costs remain. Large investments in fixed assets lead to excess capacity during low demand periods and high overhead costs (Parmigiani, 2007; Carlton, 1979; Adelman, 1949). The outsourced platform technology allows small firms to scale production seamlessly, making them resilient to demand fluctuations. We show that the value of the platform technology increases with the likelihood of negative demand shocks. As a result, the measure of outsourcing firms increases as the probability of low demand increases.

Our empirical analysis relies on a data set not previously used for these purposes: the European Investment Bank Investment Survey (EIBIS), an annual survey of non-financial companies in all EU countries started in 2016. Since 2019, EIBIS includes a specific question on the active use of digital platform technologies in the service sector, defined as a technology allowing firms to interact with customers, create digital communities or sell products and services. This data allows us to analyse the impact of digital platform usage on firm productivity within the service sector, making EIBIS unique in providing firm-level evidence on the use of platforms various industries, countries, and time periods.

To address potential endogeneity concerns – where firms' inherent productivity influences their likelihood of adopting digital platforms – we employ instrumental variables (IV). Our first instrument is based on digital platform adoption rates in the same sector but different geographical locations – we use lagged adoption rates of the same digital technologies by US firms using EIBIS data. The second instrument is regional mobile internet download speed, sourced from Ookla's Speedtest dataset. These IVs are presumed to affect platform adoption without directly influencing firm productivity.

Overall, we find significant differences in the impact of platform adoption between smaller and larger firms. Our OLS estimates show that platform adoption is associated with an average increase in labor productivity of 3.4% to 5.1%, depending on the specification. Notably, smaller firms experience a more pronounced productivity boost, with increases between 6.5% and 10.5%. This finding challenges the expectations of a standard endogeneity bias, which predicts a larger estimated impact for larger firms. Since larger and more productive firms are more likely to adopt IT, endogeneity bias would typically inflate the estimated effects for these firms. Yet, our results suggest the opposite, highlighting the disproportionate benefits smaller firms derive from platform adoption. When we control explicitly for the endogeneity of the platform adoption decision, these differences between small and large firms are even more pronounced. This suggests that, consistent with our theoretical model, firms with lower productivity have more incentives to adopt platforms in the first place.

Moreover, we find that the positive impact of platform usage on firm productivity is stronger in industries with significant demand fluctuations. This supports our argument that platforms enable firms to operate with lower fixed production costs. We provide some direct evidence that the ratio of fixed costs to sales decreases with platform usage – although the estimates are inconclusive in the econometric specifications designed to address endogeneity concerns.

Our theoretical framework and empirical results are relevant to multiple areas of the literature. First, our paper contributes to the literature on economies of scale and demand-side externalities in winner-takes-most markets by providing a novel angle. While much of the existing research highlights the dominance of larger firms and the power asymmetry in platform markets (Zhu and Liu, 2018; Parker and Van Alstyne, 2005; Rochet and Tirole, 2003), our findings demonstrate that platform adoption can actually level the playing field in adjacent markets by disproportionately boosting the productivity of smaller firms. This provides a counterpoint to the prevailing view that platforms mainly benefit larger players, showing how in complementary markets, smaller firms can leverage platforms to overcome inherent disadvantages.

Second, our paper contributes to the growing literature on the strategic implications of market frictions by examining how platform adoption alleviates these frictions (Mahoney and Qian, 2013), particularly those associated with outsourcing, and disproportionately benefits smaller firms. While prior work has examined how platforms address frictions to enable higher effort from suppliers and support welfare-enhancing equilibria through supplier-restriction strategies (Chu and Wu, 2023), as well as how frictions affect value creation and capture at the industry, firm, and resource levels (Chatain and Mindruta, 2017; Chatain and Zemsky, 2011), this study extends the conversation by focusing on the firm-size dimension of frictional impacts. Our work broadens the application of market friction theories, highlighting their role in shaping firm heterogeneity and productivity outcomes within the platform economy.

Third, our work adds to the literature on the ability of digital platforms to expand product variety and lower barriers to entry. While previous studies (Waldfogel, 2017; Brynjolfsson et al., 2006) have shown how digitization benefits smaller firms by increasing product creation and availability, our paper goes further by quantifying the productivity gains for smaller firms that adopt digital platforms. This contribution provides new evidence for the efficiency improvements enabled by platforms, complementing existing studies that focus on market access, such as Greve and Song (2017).

Finally, our study contributes to the broader literature on the relationship between information and communication technology (ICT) and firm productivity. While prior research (Schivardi and Schmitz, 2019; Kretschmer, 2012) has examined the positive impact of ICT on productivity at both country and firm levels, our paper offers specific insights into the mechanisms by which platforms drive these gains, particularly for smaller firms. By identifying how platform usage alters the fixed cost structure and increases efficiency, our paper deepens our understanding of the pathways through which ICT can boost firm performance, especially for firms that traditionally operate at a productivity disadvantage.

2. Platforms reduce the cost of outsourcing

Internet platforms reduce the cost of making transactions and hence facilitate outsourcing. As we discuss next, this reduction favor particularly smaller firms for whom the cost of undertaking an investment to insource a particular function is higher.

Following the framework in Milgrom and Roberts (1992) as used in Garicano and Kaplan (2001), platforms impact transaction costs. These are of two kinds. First, *coordination costs*, which are those that are required to manage and synchronize the activities of different parties involved in a transaction. We differentiate two types of coordination costs, process improvements and increases in market place efficiency and reach. Second, *motivation costs*, which arise from the need to align the interests of different parties involved in a transaction and ensure compliance with the terms of the contract. While large firms could gain these efficiencies by undertaking large investments, platforms allow smaller firms to gain these efficiencies through outsourcing – given their scale, they could not attain them through their own investment.

2.1. Coordination costs

Process improvements: automatization, AI and integration. Digital technologies, particularly internet platforms, reduce the cost of connecting different agents and of processing information (Chu and Wu, 2023; Parker et al., 2017; Hagiu, 2009). They also enable the automation and simplification of repetitive tasks. Without platforms, these improvements require fixed investments, often unattainable to small firms. For instance, customer relationship management platforms like Salesforce.com streamline customer interactions and automate repetitive tasks, improving efficiency. They provide centralized data management, analytics, and integration with other business tools. They also enable personalized interactions with customers, enhancing customer satisfaction and loyalty.

Small business can more easily access and use advanced technology through platform services. Data analytics, AI and machine learning, which once required significant investment in skills and technology, are accessible through platforms offering these as part of their package of services. This is the case, for instance, of cloud services like Amazon Web Services and Microsoft Azure which not only eliminate the need for physical IT infrastructure, reducing upfront and maintenance costs and increasing scalability and reliability, but also offer integration with advanced IT tools, including AI and machine learning.

Similarly, ad tech platforms like as Google Ads and Meta Business Manager simplify and automate the process of creating an advertising campaign, but also offer live analytics for real-time campaign adjustments and integration with other marketing tools. Additionally, platforms enable small businesses to offer more services by integrating various digital tools. For instance, a customer management service might incorporate messaging and payment systems, allowing a small business to provide a seamless experience to its customers without the need to develop these systems in-house.

Marketplace benefits: increased reach and improved matching. Internet platforms not only lower cost on existing transactions and processes, but allow firms to carry out transactions that would not have occurred otherwise, expanding market reach and efficiency (Chatain and Mindruta, 2017; Chatain and Zemsky, 2011; Li and Netessine, 2020). For instance adtech platforms enable businesses to reach a global audience and to personalize ads for specific target groups using AI tools. An e-commerce platform like Zalando can sell fashion and lifestyle products to a global audience. Similarly, Amazon or eBay enable a small shop to sell products to customers across the globe (Hortaçsu et al., 2009), something that would be much harder and more costly without such a platform.

Digital market platforms also facilitate procurement, by enabling access to a global marketplace of suppliers, promoting transparency, standardization, and efficiency. This allows for benefits such as wide product variety, streamline sourcing processes and centralizing purchasing activities.

Similarly, LinkedIn offers a space for small firms to network and recruit talent without the need for extensive human resources departments. Hence small firms can access global talent pool. This enables them to recruit specialized skills at affordable costs. Different platforms cater to various job types, enhancing matching quality. For instance, Welcome to the Jungle allows firms to represent their own brands in their own pages; Indeed offers a basic, free service for posting openings; Manatal integrates recruiting with social media companies.

2.2. Motivation costs

Reductions in Informational Asymmetries. Platforms that offer user reviews provide a way for smaller firms to build a reputation online (Che and Hörner, 2018; Chevalier and

Mayzlin, 2006; Cui et al., 2020; Li and Netessine, 2020; Pavlou and Gefen, 2004). Traditionally, only large business could circumvent information asymmetries concerning their quality by building reputations through brands. A customer could safely stay in a hotel, if it was, say, a Hilton, or in a McDonald's restaurant. Now, rating and review mechanisms digital platforms attract new costumers without requiring established brand recognition, thereby leveling the playing field with larger competitors.

Moroever, the owners of the marketplace regulate market interactions, managing incentives and information asymmetry to enable positive network effects. This is true for physical market places since medieval times – as Fishman and Sullivan (2016) illustrate in the case of Medieval Fairs, with the count of Champagne as market designer "inviting the right sorts of participants (and more importantly, keeping the wrong sorts away), setting the rules, and punishing transgressors, ensuring a safe and reliable place that was much valued by merchants in a medieval Europe that was fraught with peril." In this way, the platform owners are the "regulators" of these marketplaces (Boudreau and Hagiu, 2009; Chu and Wu, 2023).

Reduction in commitment and contracting costs. Platforms typically enforce standardized contracts, terms of service, and dispute resolution mechanisms, reducing the need for custom legal agreements and minimizing negotiation complexities (Constantinides et al., 2018). By operating through established platforms, small firms can often rely on the platform's compliance with local regulations, reducing the risk and cost of legal issues. Platforms may also offer guarantees or insurance that protect against non-performance or other contract breaches. For instance, Airbnb provides a resolution center where hosts and guests can resolve disputes as well as insurance coverage, information on local rules and regulations, and tax collection and compliance.

3. Theory: Platform, firm size and productivity

3.1. A simple model of technology choice

In the previous section, we documented large reductions in transaction costs associated with the use of platforms, which reduce the cost of outsourcing. We now study theoretically the relation between insourcing, outsourcing and productivity. We do this in the simplest possible model.

A firm facing a downward sloping demand curve (the firm is a monopolist or produces in monopolistic competition[3]) must choose between one of two technologies: outsourcing certain functions, and thus reducing its fixed costs but increasing variable costs (a range of transaction costs), or insourcing them, and hence building a fixed cost structure (think IT and talent) that allows it, by virtue of being customised to the needs of the firm rather than generic, to later produce with lower variable costs (Poppo and Zenger, 1998). We show that firms below a threshold of productivity choose low fixed cost, high variable cost technologies (they "outsource"), and firms above the threshold use high fixed cost technologies (they "insource").[4]

There exists a continuum of firms with idiosyncratic (firm-specific) productivity $\alpha \in [\underline{\alpha}, \overline{\alpha}]$. Productivity is also affected by technology t. Producers use a linear technology to transform the composite input n with costs c^t into output x:[5]

$$x = \alpha n \tag{1}$$

or $n = x/\alpha$.

Firms can choose one of two technologies $t \in \{t_I, t_O\}$ with variable cost c^t and fixed cost F^t:

- **Technology I (t_I):** Insourcing with fixed cost $F^I = F$ and variable cost $c^I = c$.
- **Technology O (t_O):** Outsourcing with fixed cost $F^O = F - \Delta$ and variable cost $c^O = \tau c$, where $\tau > 1$.

$\tau > 1$ reflects the range of Coasian costs of market transactions as described above – informational asymmetries, completing contracts, processing information, reaching customers and providers. F^t is larger when insourcing since firms must invest in customising their own solutions. Given our linear production function, variable cost is given by c^t/α. Hence variable cost differences reflect technology choice and productivity differentials.

The cost function of a firm with productivity α that chooses technology t is:

$$C^t(\alpha) = F^t + \frac{c^t x}{\alpha}$$

Finally, we assume consumers have constant elasticity of substitution preferences so that their optimization results in a constant elasticity demand function, $x(p) = kp^{-\varepsilon}$.

[3]The oligopolistic case, when the game features strategic complementarities in the choice of technology, can be analyzed using the results on supermodular games (Vives, 1990).

[4]Formally, the model builds on the two technology choice in Bustos (2011) generalized in Reichardt (2024).

[5]We follow De Loecker and Syverson (2021) in our simple treatment of productivity.

Given all of the above, the profit function is:

$$\pi^t(\alpha) = px(p) - \frac{c^t}{\alpha}x(p) - F^t \tag{2}$$

Proposition 1. *Suppose that in equilibrium, some firms choose insourcing (high fixed cost, low variable cost) and some choose outsourcing (low fixed cost, high variable cost). Then there exists a threshold α^* such that all firms $\alpha \geq \alpha^*$ (high productivity firms) choose insourcing, and firms $\alpha \leq \alpha^*$ (low productivity firms) choose outsourcing. Moreover, outsourcing firms are smaller.*

Proof. First, note that the choice of p is such that

$$\frac{\partial \pi_i^t}{\partial p} = 0$$

which yields optimal price:

$$p^* = \frac{c^t}{\alpha}\frac{\varepsilon}{(\varepsilon - 1)} \tag{3}$$

(recall that $\varepsilon > 1$ is a condition for optimality) and quantity

$$x^* = k\left[\frac{\alpha}{c^t}\frac{\varepsilon - 1}{(\varepsilon)}\right]^{\varepsilon} \tag{4}$$

And replacing it in the profit function and simplifying, we have that the optimized profits are:

$$\pi^{t*} = \kappa\left(\frac{\alpha}{c^t}\right)^{\varepsilon-1} - F^t \tag{5}$$

where $\kappa = k(\varepsilon - 1)^{\varepsilon-1}\varepsilon^{-\varepsilon}$. The difference between insourcing and outsourcing is given by:

$$\pi^I(\alpha) - \pi^O(\alpha) = \kappa\left(\frac{\alpha}{c}\right)^{\varepsilon-1}\left(1 - \frac{1}{\tau^{\varepsilon-1}}\right) - \Delta$$

The first term is positive, since $\tau > 1$ and $\varepsilon > 1$. It is also increasing in α for the same reason. A firm α^* is indifferent between insourcing and outsourcing if:

$$\alpha^* = c\left[\frac{\Delta}{\kappa\left(1 - \frac{1}{\tau^{\varepsilon-1}}\right)}\right]^{\frac{1}{\varepsilon-1}}.$$

A necessary and sufficient condition for α^* to exist is that some firms choose insourcing, that is $\overline{\alpha} > c\left[\frac{\Delta}{\kappa\left(1-\frac{1}{\tau^{\varepsilon-1}}\right)}\right]^{\frac{1}{\varepsilon-1}}$, and some other firms choose outsourcing: $\underline{\alpha} < c\left[\frac{\Delta}{\kappa\left(1-\frac{1}{\tau^{\varepsilon-1}}\right)}\right]^{\frac{1}{\varepsilon-1}}$. □

Note that we can characterize the impact of all parameters on the choice of technologies by inspection. In particular, the threshold α^* increases when the fixed cost of insourcing Δ increase, and when transaction costs τ decrease.

Corollary 1. *The measure of outsourcing firms* $[\alpha^* - \underline{\alpha}]$ *increases when:*

1. *Fixed costs of insourcing* Δ *increase.*
2. *Transaction costs* τ *decrease.*
3. *Variable costs* c *increase.*

Previous literature has demonstrated how adopting a platform as an organizational mode facilitates outsourcing and shifts production from within the firm to outside, where third parties create much of the value (Benzell and Brynjolfsson, 2019; Parker et al., 2017). Our interpretation of the evidence presented in the previous section is that improvements in internet platforms reduce the cost of outsourcing, thereby decreasing τ. The consequences follow straightforwardly.

Proposition 2. *A reduction in the cost of making market transactions* τ *has the following impact:*

1. *Increases the measured total factor productivity of small firms.*
2. *Reduces the price chosen by small firms.*
3. *Increases the quantity produced by small firms.*

Proof. To show proposition (2.1), define total factor productivity of firm with idiosyncratic productivity α as the idiosyncratic productivity divided by the measured variable cost (which is itself a consequence of the choice of technology) $TFP = \frac{\alpha}{c^t}$. This is the amount of output generated by one unit of cost. Since the cost of the small (outsourcing) firms is $c^t = c^O = \tau c$, productivity increases for smaller firms. Results (2.2) and (2.3) follow straightforwardly from recalling that $c^t = \tau c$ in equations (3) and (4). □

3.2. Stochastic Demand: Platforms as insurance

We now extend the model to include stochastic demand. Firms invest in fixed assets, resulting in excess capacity during low demand periods and high overhead costs. The advantage of outsourced “platform” technology is that it makes (small) firms resilient to fluctuations in demand, allowing seamless production scaling. Whether demand surges or drops, firms using this technology can match demand at any scale, leading to a flatter profit function with constant returns to scale, ensuring optimal capacity utilization despite large demand variations.

We set up a simple extension of the above model to capture this idea: demand is zero with probability $1-q$. Variable costs are not incurred if demand is zero, but fixed costs are always incurred. The profit function in equation (2) becomes:

$$\pi_q^t(\alpha) = qpx(p) - q\frac{c^t}{\alpha}x(p) - F^t \tag{6}$$

From this, we derive two results:

Proposition 3. *Suppose demand is stochastic so that with probability* $(1-q)$ *demand is 0. Then:*

1. *The outsourcing technology is more valuable the higher the probability of a negative shock.*
2. *The measure (losely, the “number”) of outsourcing firms* $[\alpha^* - \underline{\alpha}]$ *increases with the likelihood of a negative shock.*

Proof. Including the parameter q:

$$\pi_q^I(\alpha) - \pi_q^O(\alpha) = q\kappa\left(\frac{\alpha}{c}\right)^{\varepsilon-1}\left(1-\frac{1}{\tau^{\varepsilon-1}}\right) - \Delta$$

This expression increases with q, so that the outsourcing technology is more valuable when shocks are more likely ($1-q$ grows).

Solving for the threshold idiosyncratic productivity:

$$\alpha_q^* = c\left[\frac{\Delta}{q\kappa\left(1-\frac{1}{\tau^{\varepsilon-1}}\right)}\right]^{\frac{1}{\varepsilon-1}}.$$

The threshold α_q^* decreases in q, conversely, it increases in the probability of low demand realization $1-q$. □

To understand the logic, suppose a pure platform technology existed, completely eliminating fixed cost. The profit function would simply be:

$$\pi_q^t(\alpha) = qpx(p) - q\frac{c^t}{\alpha}x(p) \tag{7}$$

and q scales up and down the profit function *linearly* a constant returns to scale technology in q.

Basically, the outsourcing (platform), technology flattens the profit function, making it more linear and resilient to potential drops in demand, as it enables firms to adjust production scales seamlessly.

4. Data

We use data of the European Investment Bank Investment Survey (EIBIS), an annual survey initiated in 2016 encompassing approximately 12,000 non-financial corporations across the EU. This survey employs a stratified random sampling method, targeting firms in all 27 EU countries.[6] Since 2019, EIBIS also covers a sample of 800 firms in the US to compare investment dynamics in Europe and the US. The respondents to the interviews are senior managers or financial directors with responsibility for investment decisions and how investments are financed - for example, the owner, chief financial officer or chief executive officer. Brutscher et al. (2020) provide evidence that EIBIS is representative of the business population in the EU as described by Eurostat Structural Business Statistics.

The 2019 wave of EIBIS introduced a specific question regarding the active use of digital platform technologies by firms in the service sector. A digital platform is defined in the survey as a technology allowing firms to interact with customers, create digital communities or sell products and services. Leveraging this question, our analysis centers on assessing the influence of platforms on firm productivity within the service sector. To our knowledge, EIBIS stands as the sole available dataset offering firm-level insights into digital platform service usage spanning various industries, countries, and temporal dimensions.

EIBIS encompasses a wide array of firm characteristics, including turnover, number of employees, and age, alongside financial data. Additionally, it captures qualitative insights into the firm's perceptions regarding managerial capabilities, investment constraints, and

[6] The EIBIS sample is stratified disproportionally by country, sector and firm size class, and proportionally by region within each country. The firms have at least five employees, with both full-time and part-time employees being counted as one employee, and employees working less than 12 hours per week being excluded. An enterprise is defined as a company trading as its own legal entity. As such, branches are excluded from the target population. However, the definition is broader than in a typical enterprise survey given that some company subsidiaries are their own legal entities.

investment behavior. To supplement this self-reported data, we also leverage administrative financial data from Bureau van Dijk's Orbis on balance sheet and profit and loss accounts.

The comprehensive nature of the EIBIS survey enables the direct measurement of firm-level platform adoption across industries, a novel feature within the empirical literature on platform usage. Prior studies that have investigated the impact of platform adoption on firm performance have predominantly relied on data from single industries (Lewis and Reiley, 2014) or utilized proxies for adoption estimated at the industry level (Gal et al., 2019).

Dependent variable. Our objective is to assess the impact of firm usage on firm productivity. Due to limitations in the EIBIS data, which only covers platform usage in service industries starting from 2019, we face challenges in estimating total factor productivity using long time series required for calculating firm capital stock based on past investments. As an alternative, we opt to employ labor productivity as a proxy for firm productivity. Our analysis focuses on labor productivity, defined as the ratio of firm turnover to the total number of employees, obtained from variables that are self-reported by firms in EIBIS. As a robustness excercise, we utilize turnover and number of employees reported in Orbis. In addition, we also report results with total factor productivity instead of labor productivity using data on value added, fixed assets and the cost of intermediate inputs from Orbis. Notably, results derived from these alternative approaches are qualitatively similar to those obtained using labor productivity in EIBIS.

Explanatory variables. The survey asks firms operating in service industries whether they actively use digital platforms such as Amazon, Alibaba, Ebay to interact with customers, create digital communities or sell products and services. We use an indicator variable taking value one if the firms report to actively use digital platforms, and zero otherwise. We investigate whether the use of platforms has a higher impact on smaller firms by interacting platform usage with firm size. Since our dependent variable uses the number of employees in the denominator, we utilize as proxy of firm size the self reported value of fixed assets in EIBIS.[7] Our results remain unchanged if instead we use the value of fixed assets reported in Orbis.

Control variables. In our empirical framework, it is crucial to account for variables influencing labor productivity that may also be correlated with firm platform usage. Previous research indicates that managerial practices significantly impact firm productivity (Bender

[7]EIBIS asks firms to report the value of the business' total fixed assets. It specifically asks to include tangible assets (e.g. buildings, equipment, vehicles) and intangible assets (e.g. patents, trademarks and copyright) but to exclude financial assets such as cash or bank accounts.

et al., 2018). Consequently, we include a control variable that takes value one when the firm has adopted a business strategy monitoring system that compares the firm's current performance against a series of strategic key performance indicators.

We control for firm age using an indicator variable taking value one when the firm is less than 10 years old firm. We account for the number of employees using four firm size categories: microenteprises with 5 to 9 employees, small firms with 10 to 49 employees, medium-sized firms with 50 to 249 employees, and large firms with 250 employees or more.

Finally, we include a control variable indicating whether firms export their products or services to other countries. This control variable can be important, as there is ample evidence that exporting firms tend to be more productive (Bernard et al., 2003; Melitz, 2003). However, it is also a problematic control because the positive impact of platform on firm productivity may partly occur through enhanced market reach via exports. Therefore, in our empirical analysis, we report separate results with and without exporter status.

Table 1 reports descriptive statistics of the variables used in our empirical analysis. It shows that firms that report platform adoption tend to have higher labor productivity and are larger in terms of turnover, employees and fixed assets. Additionally, they are more likely to use strategic business monitoring systems and export their products and services to a foreign country. On the contrary, platform usage does not seem to be correlated with firm age. Overall, Table 1 points out to the importance of the control variables when estimating the effect of platform on firm productivity.

5. Empirical strategy

In our empirical analysis, we estimate the equation:

$$y_{ijct} = \alpha_j c + \alpha_t + \beta Platform_{ijct} + \gamma Size_{ijct} + \sigma Platform_{ijct} * \ Size_{ijct} + \lambda X_{ijct} + \varepsilon_{ijct} \quad (8)$$

where the dependent variable, y_{ijct}, refers to productivity of firm i in sector j operating in country c at time t. $Platform_{ijct}$ captures the active use of digital platforms and $Size_{ijct}$ the value of fixed assets. The vector, X_{ijct}, includes control variables, α_{ct} denotes country-sector fixed effects, α_t denotes year fixed effects, and ε_{ijct} is a random disturbance term. Our main parameter of interest σ is for the interaction term between platform and firm size. It captures how the relationship between the binary variable $Platform_{ijct}$ and firm productivity varies with firm size.

We include country-sector (α_{jc}) and year (α_t) fixed effects in all our regressions, so that we remove from our estimates the effect of time-specific and time-invariant country-sector (e.g. industry technology intensity) confounding factors that may bias the estimation of the relationship between platform adoption and productivity.[8] Our estimates should be interpreted as cross-sectional differences in firm outcomes within country-sector pairs that are driven by platform adoption.

The decision for a firm to adopt digital technologies is likely associated with its inherent productivity, even when accounting for country, sector, year, and firm-specific characteristics. More productive firms tend to embrace digital technologies and invest in intangible assets, as both are often indicative of superior managerial skills, organizational capacity, or stronger financial resources. Moreover, common factors may influence both productivity and digital adoption. For instance, firms with stronger management practices are inclined to adopt new technologies (Nicoletti et al., 2020), potentially enhancing productivity as a result (Bloom et al., 2012). Failure to adequately address this correlation could result in an overestimation of the relationship between platform adoption and productivity. Conversely, as we have described in our theoretical model above, platforms may offer productivity enhancements that are particularly attractive to less productive firms. Neglecting this negative correlation could lead to an underestimation of the relationship between platform adoption and productivity.

The EIBIS survey does not have panel data that follows the same set of firms across time. If that was the case, we could add firm fixed effects to alleviate some of these endogeneity concerns. In our sample this is not feasible because the majority of firms are not interviewed in two consecutive years.[9] EIBIS data can be thus interpreted as a repeated cross-section of firms, where the panel component is short and small.

Instead, we address endogeneity using instrumental variables to try to correct for the correlation between a firm's inherent productivity and platform adoption. The instrumental variables that we use vary at the level of sector and geography. First, we assess the adoption rates of firms operating in the same sector but in different geographical locations. As the EIBIS survey predominantly covers firms in the 27 EU countries, we rely on data regarding the use of digital platforms by US firms operating in the same sector in the previous year, as reported in the same EIBIS survey. Lagged adoption of platforms by US firms within the

[8]We control for the 27 EU countries and for sectors in services at NACE 1 digit level with 4 different categories: G. Wholesale and retail trade, repair of motor vehicles and motorcycles; H. Transportation and storage; I. Accommodation and food service activities; J. Information and communication. We also control for the interactions of country and sector. The years included in the analysis are 2020 to 2023.

[9]About 40% of firms in EIBISare interviewed in two consecutive and some 15% are interviewed in three consecutive years.

same sector should be correlated with the use of platforms by EU firms but a priori should be independent of firm omitted variables that may drive individual firm productivity.

Furthermore, for successful integration of available and suitable digital platforms, a firm necessitates a stable and high-speed internet connection. Operating in regions with lower internet connectivity may pose challenges to the adoption of platform technologies. Lack of internet access should be negatively correlated with platform usage but there is a priori no reason to expect that bad internet connection at the regional level is correlated with omitted firm level variables that explain firm productivity. For confidentiality reasons and to preserve the anonymity of the firms covered by the survey, EIBIS data does not provide us the exact name, address or location of the firm, but it reports the region in which the firm is located at the NUTS 3 level.[10] Hence, our instrumental variable incorporates variation in geographical mobile download speed sourced from Ookla's Speedtest open-source dataset.[11]

Given that platform adoption, our main explanatory variable of interest, is a binary indicator, we employ a three-stage procedure with the two instrumental variables. Implementing two-stage least squares (2SLS), the conventional method for instrumental variables with continuous dependent variables, using a nonlinear first stage to predict the probability of adoption would result in a forbidden regression and inconsistent estimates (Angrist and Pischke, 2009). The solution lies in modeling the estimation process in three stages, as outlined by Wooldridge (2010, p.938) and Angrist and Krueger (2001). In the initial stage, we estimate platform adoption as a logistic function of the instrumental variables and the set of controls. From this model, we derive the fitted probabilities used as instruments in a traditional two-stage least squares method together with our two instrumental variables.

Our identification strategy relies on the assumption that firms operating in industries and regions with higher rates of digital platform adoption and faster internet speed are not significantly impacted by other productivity shocks or trends that may concurrently affect both digitalization and productivity. Essentially, we assume that the effects of our

[10] For statistical purposes, Eurostat classifies regions within EU countries using the NUTS classification. NUTS regions are generally based on existing national administrative subdivisions. There are some 1,125 NUTS 3 regions across all 27 EU countries. The average population size of a NUTS 3 region is between 150,000 and 800,000 habitants. Depending on their size, not all EU countries have subdivisions at the NUTS 3 level: for example, Luxembourg and Cyprus have only one NUTS 3 region, which corresponds to the country itself.

[11] Average mobile internet download speed at the regional level is based on tests performed using the website Speedtest.net and is measured in megabits per second. To compute our measure, we use all tests in the first quarter of 2019. The original data is provided at the level of Mercator tiles (approximately 610.8 meters by 610.8 meters at the equator), which is aggregated to NUTS 3 level averages, using the number of tests as weights. In total, more than 3.8 million tests of mobile download speed were conducted during the first quarter of 2019 in our data. On average, the number of tests per NUTS 3 region is 2,530.

instrumental variables on productivity manifest solely through the adoption of platform technologies.

6. Results

6.1. OLS estimates

Table 2 reports the results of estimating equation (6) using four different empirical specifications. The first column displays the results controlling for fixed assets (in logarithm) and the use of strategic business monitoring system. The second column adds four firm size categories based on the number of employees and firm age (a binary variable taking value one when the firm is less than 10 years old). Note that we cannot control directly for the number of employees because the dependent variable uses this variable in the denominator, which explains why we use firm size categories instead. The third column adds to the specification in column (1) firm age and exporter status (a binary variable equal to one if the firm reports to export products and services to another country). Finally, column 4 includes all control variables: the log of fixed assets, firm size categories, firm age and exporter status.

The OLS results in Table 2 show that the main effect of platform adoption is always positive. This suggests that firms that adopt platform technologies tend to have higher labor productivity. More interestingly, all specifications in the four different columns report how this positive link between platform adoption and productivity is negatively moderated by firm size, proxied by the value of fixed assets. The results imply that the effect of platform adoption on firm productivity is larger for smaller firms.

Table 3 summarizes the magnitude of the effect of platform usage on firm productivity according to the quartiles of the distribution of firm fixed assets. While the average impact of platform use for smaller firms shows a positive increase between 10.5% (first specification) and 6.5% (third specification), the impact for larger firms (those in the top quartile of the distribution of fixed assets) is negative with values oscillating between between -0.1% (second specification) and -7.1% (third specification).

Before moving on to our instrumental variable strategy, it is worth pointing out that the result that productivity gains are larger for smaller firms would not be expected under the standard spurious, reverse causality, alternative hypothesis to ours: if we are simply just measuring information technology, larger and more productive firms would be more likely to adopt and the coefficient on size should be positive.

6.2. Instrumental variable estimates

Table 4 reports the estimates from a logit regression using the two instrumental variables for digital platform adoption: lagged adoption of platform by US firms operating in the same sector, and internet mobile download speed in the NUTS3 region where the firm is located. The analysis controls for fixed assets, management practices, number of employees, firm age, exporter status, country-sector fixed effects, and year fixed effects. The two instruments exhibit a positive and significant effect on digital platform adoption. Intuitively, the estimates in Table 4 also shows that larger firms, firms using strategic business monitoring, younger firms and exporters are more likely to adopt platform technologies.

As explained above, we use the fitted values of platform adoption obtained from this logit estimation together with lagged US platform adoption in the same sector and internet speed in the region where the firm is located to run a 2SLS regression. In the 2SLS estimation, the use of the platform is instrumented with the fitted values from the first stage logit regression, and the interaction term "platform $\times$ log fixed assets" is instrumented with the interaction term of "fitted values $\times$ log fixed assets".

Table 5 reports the 2SLS estimates. As with the OLS results of Table 2, the different specifications show that the effect of platform adoption on firm productivity is positive, while the interaction with firm assets has a negative coefficient. These results present further evidence that the effect of platform on firm productivity is smaller for larger firms.

Compared to the OLS estimates in Table 2, the magnitude of the coefficients reported in Table 5 are significantly larger than the ones in Table 2. For instance, if we focus on our main specification (column 2), the effect of platform use in Table 5 is 1.344 compared to 0.513 in Table 2. These results illustrate a downward bias in the OLS estimates, suggesting that firms with lower productivity (i.e. smaller firms) may be precisely those with higher incentives to adopt platforms. Similarly, the interaction of platform use with firm assets is -0.039 in column 2 of Table 5, while it is is -0.034 in Table 2.

Table 6 summarizes the magnitude of the impact on platform productivity using the 2SLS estimates of Table 6. For small firms, the estimated impact on productivity varies between 60.3% and 89.7%, while for larger firms the estimates fluctuate between 28.5% and 73.2%. This implies that the negative impact of firm size on the effect of platform on productivity seems to be significantly larger once we account for the endogeneity of platform adoption.

7. Robustness tests and evidence on the mechanism

In this section we test the robustness of our results using other measures of firm productivity as dependent variable. Instead of using labor productivity, we use estimates of total factor productivity (TFP) that are also widely used in the literature (Kretschmer, 2012). First, we estimate firm production functions using EIBIS data on sales as firm output, and number of employees and fixed assets as inputs, in OLS regressions separately for each sector.[12] TFP in EIBIS is estimated as the residual of the production function equation. Second, we cross the EIBIS dataset with Orbis data to replicate our results but using labor productivity estimated using information coming from balance sheets and profit and loss acounts rather than the self-reported variables in the EIBIS survey. Third, we use Orbis data, which report information on material costs, to estimate TFP using a control function approach. In particular, we follow Ackerberg et al. (2015) and use firm value added as the dependent variable, number of employees and fixed assets as inputs, and material costs in the first stage control function.

Tables 7 to 10 replicate our main results with these different dependent variables. Our results based on TFP or labor productivity using Orbis variables are qualitatively similar to those reported in column 2 of Tables 2, 3, 5 and 6. Again, platform adoption seems to have a larger (and positive) effect on the firm productivity of smaller firms.

Next we explore the mechanisms behind our firm productivity results. In our theoretical model above, we have argued that platform adoption allows firms operating with a lower fixed costs of production and this could explain improvements in firm productivity. We explore whether this is indeed the case by analyzing the relationship between the ratio of firm total assets over firm sales as a function of platform, using the same control variables as in our previous empirical specifications.

The OLS estimates of Table 11 show how platform use is associated with lower assets to sales ratio and how this effect is stronger for smaller companies. The first column uses all firms, while the other columns report the estimates for different samples based on the number of employees. We do not use fixed assets in the regressions because it is highly correlated with total assets (the denominator in the dependent variable). The magnitude of the effects of platform use are relatively large. The results in column 3 of Table 11 show that for small companies platform adoption is associated with a 3% decrease in the asset to sales ratio. This decrease in the use of fixed assets means that keeping constant the profit

[12] We cannot use a control function approach based on intermediate inputs (Ackerberg et al., 2015; Levinsohn and Petrin, 2003) because EIBIS does not have information on material costs.

margin, Return on Assets (ROA) should increase by three percentage points. Given that the average ROA in our sample is 12%, then an increase of 3% represents a 25% increase in profitability associated with platform adoption. Table 12 shows the estimates of 2SLS regressions using total assets over sales as dependent variable. Overall, the results are mixed and very imprecise. The standard errors are large and prevent us from finding positive or negative results that are statistically significant.

Finally, to assess whether platforms allow firms to better adapt to sudden changes in demand, we construct an index of sales variability in the sector in which firms operate. This index is based on Eurostat short-term statistics on monthly sales and turnover in the services and trade sectors.[13] A higher value of the index means that sales in the sector tend to have higher variability. The index is matched to EIBIS firms at the level of country and sector.

The first column in Table 13 reports the results of OLS regressions using the index of sales variability interacted with the use of platforms. They are very close to our main results reported in column 2 of Table 2. For example, the interaction term of platform and firm size (proxied by the log of fixed assets) is -0.033 in Table 13, compared to -0.034 in Table 2.[14] The estimates in Table 13 also show a positive interaction term between the use of platform and sector sales variability. In other words, platforms can help mitigate sudden changes in demand (proxied by the variability index) and this is associated with higher firm productivity. The estimated coefficient on the index of sales variability is negative but the estimates are very imprecise due to large standard errors. It is plausible that variability in sales can have a negative effect of labor productivity but we cannot conclude it directly from the estimates in Table 13.

The second column in Table 13 reports 2SLS estimates, where the interaction term "platform $\times$ index of sales variability in the sector" is instrumented with the interaction of fitted values from the first stage regression and the index itself, following what we did for other variables that we interact with platforms. As in the OLS regression, the estimated coefficient of this interaction term is positive, suggesting again that platforms can help reduce the potential negative effects of sales variabilitiy. At the same time, the magnitude of the 2SLS

[13] For each year between 2010 and 2019, we compute the standard deviation of monthly sales by country and sector. We standardise it by its annual mean to have a standardised measure of the standard deviation across countries, sectors and years. We then take the mean of this annual variable over the 10 years period 2010-2019, excluding the COVID-19 period when there was a sharp decrease in sales due to the pandemic and lockdown measures, and the strong recovery period that followed. This means that our final index does not vary over time.

[14] The magnitude of the estimated coefficient on the other variables reported in Table 13, such as the log of fixed assets, the use of business monitoring system, number of employees and firm age, are also very similar to Table 2.

estimates of the interaction term “platform × log of fixed assets” – which is at the centre of interest in this paper – is -0.034 and very similar to our main results in Table 6, where it is -0.039. Overall, we argue that the results in Table 13 show that platforms allow firms to outsource some of their activities and they can be a substitute for large investments in fixed tangible capital. They also allow firms to better adapt to sudden changes in demand.

8. Conclusion

We conclude that digital platforms are an equalizing technology, a technology that levels the playing firm in favor of smaller firms. To reach this conclusion, this paper proceeds in three steps.

First, we discuss conceptually, and on the basis of multiple examples, the changes in transaction costs due to platforms. We argue they differentially favor small firms outsourcing. For instance, a small firm, rather than hire an entire HR or a marketing department, may rely on platform tools that not only automatize a lot of the processes, but also allow the firm to access state of the art AI and data analytics technology.

Second, we make a simple theoretical argument, that, in spite of appearing first order, we have not found formalized in the literature. A firm can outsource certain functions and rely on “standard” tools in the market or invest in customized tools to produce by itself. Outsourcing allows for lower up front investment but increases variable costs. Insourcing involves large fixed investments but allows for lower variable costs. Two conclusions follow immediately. First, less productive, smaller firms, are more likely to rely on outsourcing. Second, if transaction costs drop, in particular because of improvements in internet platform technologies, the range of firms that will outsource increases, and so does their productivity.

Third, we study empirically the impact of platforms on productivity of firms of different sizes, using data from the European Investment Bank Investment Survey (EIBIS), complemented by Bureau van Dijk’s Orbis financial data. Firms that use digital platform technologies tend to have higher levels of turnover, employees, fixed assets, and labor productivity. But we also find that digital platform adoption is associated with an increase in firm productivity, with a stronger effect for smaller firms. Instrumental variable estimates confirm this larger productivity impact for smaller firms, suggesting a downward bias in OLS estimates in agreement with our hypothesis that firms with lower productivity have a higher incentive to adopt platforms.

Our results stand in contrast with a growing literature that explores how information technologies disproportionally help large firms, because of the very large investments needed. Hsieh and Rossi-Hansberg (2023) argue that IT has allowed for an industrial revolution in services, by enabling service industries to achieve economies of scale and expand geographically. Relatedly, Aghion et al. (2023) find that the driving force behind increased market concentration is the reduction in overhead costs for multiple products and a growing efficiency advantage among large firms, prompting these firms to expand into new product lines. In the same direction, De Ridder (2024) argues that the rise in intangible inputs explains increasing concentration and lower business dynamism, since intangibles reduce marginal costs and raise fixed costs, giving high-intangible firms a competitive advantage. Lashkari et al. (2024) use detailed French level data to show that the large drop in the price of IT explains the drop in concentration and the increase in the aggregate labor share in France.

In contrast, we conclude that while IT investments are large-scale biased – to use the terminology of Reichardt (2024) – in the sense that their large physical and human capital requirements favor large firms and lead to increasing industry concentration, platforms potentially level the playing field by facilitating the access of smaller firms to these same technologies.

It is worth stressing that a large literature has discussed the anticompetitive effects raised by dominant platforms and the asymmetric power they enjoy (Cabral et al., 2021; Zhu and Liu, 2018; Miric et al., 2019). We do not disagree these effects exist. Our work abstracts from them and investigates, at given market prices, the productivity gains that can be obtained by firms using these platforms. We show that platform adoption can level the playing field by altering relative size advantages and significantly boosting the productivity of smaller, less productive firms. Our findings are in line with previous findings within content industries. As Waldfogel (2017) summarizes, "digitization has increased the number of new products that are created and are available to consumers." Brynjolfsson et al. (2006) and Oberholzer-Gee and Strumpf (2007) find that the internet and digital platforms have facilitated consumer access to niche products, referred to as the long tail, and Greve and Song (2017) argue that Amazon's self-publishing platform has dramatically shifted power from large publishers to smaller publishers and independent authors.[15]

Our analysis is necessarily partial equilibrium. A monopoly platform could potentially

[15] This is not a settled view in the study of content industries, as some other findings in content industries suggest platform adoption can favor larger players, leading to a more asymmetric distribution of success. Meyer et al. (2024) find that larger publishers gain more from platform aggregators. Rietveld et al. (2020) show that platform dominance increases sales concentration among a few successful complements, and Fleder and Hosanagar (2009) find that recommendation systems can reduce sales diversity. Skiti et al. (2022) support this view, noting that products with limited data struggle to rank highly on platforms.

lead to a new economy-wide equilibrium where no firm can operate without a platform e.g. for reservations. In this world, an individual firm would have higher productivity by adopting, given its rivals adopt, but a large set could be better off without them or their competitors offering the platform. Our study cannot consider this effect.

In terms of limitations we have utilized a broad interpretation of transaction costs (including both coordination and motivation costs) that goes back to Coase (1937) through Milgrom and Roberts (1992). As Coase (1937) put it, "the operation of a market costs something and by forming an organization and allowing some authority (an "entrepreneur") to direct the resources, certain marketing costs are saved." In this regard, our conceptualization of transaction costs aligns entirely with the concept of market friction as introduced by Mahoney and Qian (2013) and utilized in Chu and Wu (2023); Chatain and Mindruta (2017) and Chatain and Zemsky (2011). Hence we do not take the more narrow view of the property rights theory of the firm as the allocation of residual control rights under incomplete contracting. In our discussion, incomplete contracts, together with informational asymmetries and some more simple "Coasian" process and market costs, are part of the cost of using the price mechanism, and reducing them allows for more outsourcing, and hence increases the productivity of smaller firms. Of course, as the literature has pointed out, transaction costs do not magically disappear by moving into firms – our model emphasizes the need to invest to obtain similar efficiencies. Moreover, as a large literature has argued, the distinction between transaction and production costs is not as neat as Coase (1937) would have it. And yet we find the concept useful. Consequently, we rely on the reader keeping in mind a broad interpretation of these terms.

Along the same lines by focusing only in the role of platforms in reducing the market frictions needed to outsource operation and operate with lower fixed costs but higher variable costs we are abstracting from a well-known literature that has already investigated other determinants of the make versus buy decision. Argyres and Zenger (2012) have argued how the degree of complementarity among distinct firm assets and capabilities can be a key driver of outsourcing decisions. In general, we have also abstracted from the role that firm heterogeneity, particularly differences in their specific bundles of capabilities, may play in our analysis. The interaction between firm capabilities and platform adoption, and how these capabilities influence the productivity gains of smaller firms, remains an open question. Future research could explore how variations in firms' capabilities shape the extent to which platforms enhance productivity, offering valuable insights into the mechanisms at play.

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Table 1 – Descriptive statistics

	Firms not using digital platforms	Firms using digital platform
Labor productivity (Turnover per employee)	291,038	317,071
Turnover (EUR)	6,061,408	9,188,496
Number of employees	19.4	29.6
Fixed assets (EUR)	2,271,978	3,508,940
Age	27.2	26.1
Firm is less than 10 years old	15.1%	18.5%
Firm uses strategic business monitoring system	23.1%	44.1%
Firm exports goods or services to another country	26.8%	38.9%

Table 2 – Effect of platform on labor productivity as a function of firm size: OLS regressions

Dependent variable: Log labor productivity	(1)	(2)	(3)	(4)
Platform	0.648	0.513	0.541	0.422
	(0.105)	(0.105)	(0.103)	(0.103)
Platform × log of fixed assets	-0.045	-0.034	-0.039	-0.030
	(0.007)	(0.007)	(0.007)	(0.007)
Log of fixed assets	0.107	0.144	0.096	0.135
	(0.005)	(0.006)	(0.005)	(0.006)
Use of business monitoring system	0.134	0.171	0.105	0.144
	(0.018)	(0.018)	(0.018)	(0.018)
Number of employees (omitted category: micro 5-9 employees)				
Small (10-49 employees)		-0.045		-0.073
		(0.023)		(0.022)
Medium (50-249 employees)		-0.181		-0.216
		(0.029)		(0.028)
Large (250+ employees)		-0.612		-0.611
		(0.039)		(0.038)
Firm age: less than 10 years old		-0.084	-0.061	-0.081
		(0.027)	(0.027)	(0.027)
Exporter status			0.419	0.413
			(0.018)	(0.018)
Sample size	15,752	15,752	15,710	15,710
R^2	0.358	0.372	0.382	0.394

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 3 – Effect of platform on labor productivity at different values of the distribution of fixed assets. Magnitude of the effects of the OLS estimates

Dependent variable: Log labor productivity				
	(1)	(2)	(3)	(4)
Average fixed assets	0.034	0.051	0.004	0.020
	(0.018)	(0.017)	(0.017)	(0.017)
Small: 1st quartile of fixed assets	0.105	0.104	0.065	0.066
	(0.023)	(0.023)	(0.022)	(0.022)
Medium: median fixed assets	0.039	0.054	0.008	0.023
	(0.018)	(0.018)	(0.017)	(0.017)
Large: 3rd quartile of fixed assets	-0.050	-0.013	-0.071	-0.036
	(0.021)	(0.020)	(0.020)	(0.020)

Note: The table displays the magnitude of platform use on firm productivity for firms at different values of the distribution of fixed assets, using the empirical specification of Table 2. Specification (1) includes the use of business monitoring system, specification (2) adds firm size categories based on the number of employees and firm age, specification (3) adds firm age and exporter status, specification (4) adds firm size categories, firm age and exporter status. All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 4 – First stage regression: Logit regressions of platform adoption

Dependent variable: Platform adoption				
	(1)	(2)	(3)	(4)
Log of mobile download speed,	0.117	0.111	0.103	0.097
by NUTS region	(0.028)	(0.028)	(0.028)	(0.028)
Lagged use of platform in the US,	0.141	0.141	0.141	0.141
by NACE 2 digit sector	(0.028)	(0.028)	(0.028)	(0.028)
Log of fixed assets	0.017	0.008	0.016	0.007
	(0.002)	(0.002)	(0.002)	(0.002)
Use of business monitoring system	0.168	0.158	0.162	0.152
	(0.008)	(0.008)	(0.008)	(0.008)
Number of employees (omitted category: micro 5-9 employees)				
Small (10-49 employees)		0.038		0.032
		(0.010)		(0.010)
Medium (50-249 employees)		0.082		0.074
		(0.012)		(0.012)
Large (250+ employees)		0.121		0.122
		(0.017)		(0.017)
Firm age: less than 10 years old		0.034	0.029	0.034
		(0.011)	(0.011)	(0.011)
Exporter status			0.078	0.077
			(0.008)	(0.008)
Sample size	15,752	15,752	15,752	15,752

Note: The table reports average marginal effects at the mean of the variables. All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 5 – Effect of platform on labor productivity as a function of firm size: 2SLS regressions

Dependent variable: Log labor productivity	(1)	(2)	(3)	(4)
Platform	2.094	1.344	1.833	1.373
	(0.483)	(0.461)	(0.461)	(0.439)
Platform × log of fixed assets	-0.099	-0.039	-0.100	-0.064
	(0.023)	(0.023)	(0.022)	(0.022)
Log of fixed assets	0.120	0.141	0.115	0.147
	(0.013)	(0.012)	(0.012)	(0.012)
Use of business monitoring system	0.011	0.045	0.028	0.068
	(0.064)	(0.059)	(0.061)	(0.057)
Number of employees (omitted category: micro 5-9 employees)				
Small (10-49 employees)		-0.072		-0.092
		(0.027)		(0.025)
Medium (50-249 employees)		-0.243		-0.256
		(0.041)		(0.038)
Large (250+ employees)		-0.704		-0.659
		(0.059)		(0.058)
Firm age: less than 10 years old		-0.111	-0.076	-0.099
		(0.041)	(0.029)	(0.030)
Exporter status			0.375	0.372
			(0.033)	(0.032)
Sample size	15,752	15,752	15,752	15,752
F-test statistic	75.74	75.91	86.56	87.82
Cragg-Donanald Wald F-test statistic	21.89	22.17	20.75	20.62

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 6 – Effect of platform on labor productivity at different values of the distribution of fixed assets. Magnitude of the effects of the 2SLS estimates

Dependent variable: Log labor productivity				
	(1)	(2)	(3)	(4)
Average fixed assets	0.742	0.806	0.473	0.504
	(0.348)	(0.341)	(0.343)	(0.338)
Small: 1st quartile of fixed assets	0.897	0.868	0.629	0.603
	(0.352)	(0.343)	(0.345)	(0.338)
Medium: median fixed assets	0.752	0.810	0.484	0.510
	(0.348)	(0.341)	(0.343)	(0.338)
Large: 3rd quartile of fixed assets	0.555	0.732	0.285	0.383
	(0.348)	(0.345)	(0.344)	(0.343)

Note: The table displays the magnitude of platform use on firm productivity for firms at different values of the distribution of fixed assets, using the empirical specification of 5. Specification (1) includes the use of business monitoring system, specification (2) adds firm size categories based on the number of employees and firm age, specification (3) adds firm age and exporter status, specification (4) adds firm size categories, firm age and exporter status. All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 7 – Effect of platform on total factor productivity in EIBIS and Orbis as a function of firm size: OLS regressions

Dependent variable:	TFP in EIBIS (1)	Log labor productivity in Orbis (2)	TFP in Orbis (3)
Platform	0.423	0.486	0.235
	(0.088)	(0.113)	(0.098)
Platform × log of fixed assets	-0.027	-0.027	-0.012
	(0.006)	(0.008)	(0.007)
Log of fixed assets	-0.006	0.147	0.091
	(0.005)	(0.008)	(0.008)
Use of business monitoring system	0.160	0.195	0.137
	(0.016)	(0.023)	(0.018)
Number of employees (omitted category: micro 5-9 employees)			
Small (10-49 employees)	0.143	-0.046	-0.015
	(0.020)	(0.031)	(0.025)
Medium (50-249 employees)	0.218	-0.242	-0.227
	(0.025)	(0.040)	(0.035)
Large (250+ employees)	0.004	-0.721	-0.623
	(0.033)	(0.053)	(0.049)
Firm age: less than 10 years old	-0.081	0.031	0.026
	(0.024)	(0.035)	(0.028)
Sample size	15,753	7,321	6,559
R^2	0.336	0.496	0.571

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. In columns 2 and 3, log labor productivity fixed assets, number of employees and firm age are based on Orbis. Columns 2 and 3 exclude the 2023 wave of EIBIS because of missing data on sales in Orbis. Robust standard errors in parentheses.

Table 8 – Effect of platform on total factor productivity in EIBIS and labor productvity in Orbis at different values of the distribution of fixed assets. Magnitude of the effects of the OLS estimates

Dependent variable:	TFP in EIBIS	Log labor productivity in Orbis	TFP in Orbis
	(1)	(2)	(3)
Average fixed assets	0.053	0.127	0.067
	(0.015)	(0.022)	(0.017)
Small: 1st quartile of fixed assets	0.096	0.176	0.089
	(0.019)	(0.027)	(0.022)
Medium: median fixed assets	0.056	0.129	0.068
	(0.015)	(0.022)	(0.017)
Large: 3rd quartile of fixed assets	0.002	0.079	0.046
	(0.017)	(0.025)	(0.021)

Note: The table displays the magnitude of platform use on firm productivity for firms at different values of the distribution of fixed assets, using the empirical specification of Table 7. Specification (1) uses TFP in EIBIS as the dependent variable, specification (2) labor productivity in Orbis as the dependent variable, specification (3) TFP in Orbis as the dependent variable. All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 9 – Effect of platform on total factor productivity in EIBIS and Orbis as a function of firm size: 2SLS regressions

Dependent variable:	TFP in EIBIS (1)	Log labor productivity in Orbis (2)	TFP in Orbis (3)
Platform	1.248	2.631	2.682
	(0.400)	(0.785)	(0.806)
Platform × log of fixed assets	-0.036	-0.076	-0.033
	(0.020)	(0.030)	(0.034)
Log of fixed assets	-0.008	0.160	0.085
	(0.005)	(0.016)	(0.018)
Use of business monitoring system	0.043	-0.090	-0.241
	(0.053)	(0.124)	(0.118)
Number of employees (omitted category: micro 5-9 employees)			
Small (10-49 employees)	0.117	-0.093	-0.083
	(0.024)	(0.043)	(0.049)
Medium (50-249 employees)	0.159	-0.353	-0.390
	(0.036)	(0.067)	(0.076)
Large (250+ employees)	-0.080	-0.872	-0.890
	(0.052)	(0.399)	(0.118)
Firm age: less than 10 years old	-0.106	0.068	0.110
	(0.027)	(0.046)	(0.055)
Sample size	15,753	7,321	6,559

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. In columns 2 and 3, log labor productivity fixed assets, number of employees and firm age are based on Orbis. Columns 2 and 3 exclude the 2023 wave of EIBIS because of missing data on sales in Orbis. Robust standard errors in parentheses.

Table 10 – Effect of platform on total factor productivity in EIBIS and Orbis at different values of the distribution of fixed assets. Magnitude of the effects of the OLS estimates

Dependent variable:	TFP in EIBIS (1)	Log labor productivity in Orbis (2)	TFP in Orbis (3)
Average fixed assets	0.756	1.613	2.241
	(0.304)	(0.632)	(0.657)
Small: 1st quartile of fixed assets	0.813	1.753	2.298
	(0.304)	(0.640)	(0.660)
Medium: median fixed assets	0.760	1.619	2.243
	(0.304)	(0.632)	(0.657)
Large: 3rd quartile of fixed assets	0.688	1.476	2.185
	(0.307)	(0.629)	(0.659)

Note: The table displays the magnitude of platform use on firm productivity for firms at different values of the distribution of fixed assets, using the empirical specification of Table 9. Specification (1) uses TFP in EIBIS as the dependent variable, specification (2) labor productivity in Orbis as the dependent variable, specification (3) TFP in Orbis as the dependent variable. All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.

Table 11 – Effect of platform on total assets divided by sales in Orbis: OLS regressions

Dependent variable: Log total assets / sales					
Firm size category:	All	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
Platform	-0.016	-0.002	-0.030	-0.022	0.007
	(0.009)	(0.018)	(0.014)	(0.017)	(0.029)
Use of business monitoring system	0.0189	-0.010	-0.002	0.009	0.074
	(0.009)	(0.019)	(0.014)	(0.017)	(0.030)
Firm age: less than 10 years old	-0.130	-0.138	-0.111	-0.107	-0.063
	(0.013)	(0.022)	(0.021)	(0.036)	(0.048)
Number of employees (omitted category: micro 5-9 employees)					
Small (10-49 employees)	-0.037				
	(0.011)				
Medium (50-249 employees)	0.003				
	(0.012)				
Large (250+ employees)	0.074				
	(0.017)				
Sample size	10,959	2,929	3,353	3,121	1,538
R^2	0.171	0.132	0.144	0.291	0.315

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. The regressions exclude the 2023 wave of EIBIS because of missing data on total assets and sales in Orbis. Robust standard errors in parentheses.

Table 12 – Effect of platform on total assets divided by sales in Orbis: 2SLS regressions

Dependent variable: Log total assets / sales					
Firm size category:	All	Micro	Small	Medium	Large
	(1)	(2)	(3)	(4)	(5)
Platform	0.068	-0.259	1.336	-1.022	1.183
	(0.316)	(0.561)	(1.094)	(1.896)	(1.545)
Use of business monitoring system	-0.098	0.036	-0.288	0.186	-0.081
	(0.061)	(0.111)	(0.224)	(0.347)	(0.258)
Firm age: less than 10 years old	-0.133	-0.152	-0.065	-0.183	-0.046
	(0.020)	(0.025)	(0.062)	(0.100)	(0.253)
Number of employees (omitted category: micro 5-9 employees)					
Small (10-49 employees)	-0.066				
	(0.020)				
Medium (50-249 employees)	-0.050				
	(0.035)				
Large (250+ employees)	-0.004				
	(0.054)				
Sample size	7,435	2,075	2,287	2,045	1,028

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. The regressions exclude the 2023 wave of EIBIS because of missing data on total assets and sales in Orbis. Robust standard errors in parentheses.

Table 13 – Effect of platform on labor productivity as a function of firm size and an index of sales variability in the sector: OLS and 2SLS regressions

Dependent variable: Log labor productivity	OLS	2SLS
	(1)	(2)
Platform	0.424	1.037
	(0.099)	(0.493)
Platform × log of fixed assets	-0.033	-0.034
	(0.007)	(0.024)
Platform × index of sales variability in the sector	0.033	0.135
	(0.007)	(0.059)
Log of fixed assets	0.144	0.137
	(0.005)	(0.012)
Index of sales variability in the sector	-0.333	-0.328
	(0.399)	(0.354)
Use of business monitoring system	0.170	0.027
	(0.018)	(0.060)
Number of employees (omitted category: micro 5-9 employees)		
Small (10-49 employees)	-0.044	-0.073
	(0.022)	(0.027)
Medium (50-249 employees)	-0.180	-0.247
	(0.026)	(0.041)
Large (250+ employees)	-0.612	-0.714
	(0.037)	(0.060)
Firm age: less than 10 years old	-0.084	-0.113
	(0.025)	(0.031)
Sample size	15,752	15,752
R^2	0.372	

Note: All regressions include controls for the interactions of country and sector (NACE 1 digit) as well as year fixed effects. Robust standard errors in parentheses.